WIRTSCHAFTS UNIVERSITÄT WIEN VIENNA UNIVERSITY OF ECONOMICS AND BUSINESS

Infection Risk at Work, Automatability, and Employment

Abeliansky, Ana Lucia; Prettner, Klaus; Stöllinger, Roman

Department of Economics
Working Paper No. 352

Infection Risk at Work, Automatability, and Employment

Ana L. Abeliansky
Klaus Prettner
Roman Stoellinger

December 2023

WIRTSCHAFTS UNIVERSITÄT WIEN VIENNA UNIVERSITY OF ECONOMICS AND BUSINESS

Infection Risk at Work, Automatability, and Employment

Ana Abeliansky[a], Klaus Prettner[a] and Roman Stöllinger[a]

September 12, 2023

a) Vienna University of Economics and Business
Department of Economics
Welthandelsplatz 1
1020 Vienna, Austria

Abstract

We propose a model of production featuring the trade-off between employing workers versus employing robots and analyze the extent to which this trade-off is altered by the emergence of a highly transmissible infectious disease. Since workers are — in contrast to robots — susceptible to pathogens and also spread them at the workplace, the emergence of a new infectious disease should reduce demand for human labor. According to the model, the reduction in labor demand concerns automatable occupations and increases with the viral transmission risk. We test the model's predictions using Austrian employment data over the period 2015-2021, during which the COVID-19 pandemic increased the infection risk at the workplace substantially. We find a negative effect on occupation-level employment emanating from the higher viral transmission risk in the COVID years. As predicted by the model, a reduction in employment is detectable for automatable occupations but not for non-automatable occupations.

JEL classification: I14, J21, J23, J32, O33.
Keywords: Automation, robots, pandemics, viral transmission risk, occupational employment, shadow cost of human labor.

1 Introduction

What are the effects of the emergence of new transmissible diseases on employment and do these effects depend on the automatability of the affected occupations? To answer these questions, we propose a model of production in the age of automation and an emerging pandemic. This allows us to derive predictions on the employment effects of the viral transmission risk of different occupations differentiated by their automatability. Subsequently, we test the model's predictions empirically on Austrian employment data over the period 2015-2021 during which the COVID-19 pandemic increased the infection risk at the workplace exogenously.

In general, the labor market impacts of the COVID-19 pandemic have been shown to vary across workers, industries, and countries around the world (Di Porto et al., 2022; Eurofund, 2022; Blanas and Oikonomou, 2023). Apart from labor market policies, the main factors explaining the differentiated impact of the COVID-19-induced recession across socio-demographic groups, occupations, and industries are the job profiles, notably their task structure. Ding and Molina (2020) analyse the employment effects of the COVID-19 pandemic and the automation risk of occupations jointly. They argue that the pandemic and the necessary containment measures accelerated automation — a phenomenon they refer to as "forced automation".[1] In addition, regarding the task profile of occupations, Flisi and Santangelo (2022) show that both the technical teleworkability as well as the level of social interaction involved in a job were relevant for the extent of employment reductions in 2020 in the European labor market.[2] For both characteristics, teleworkability and social interaction, Flisi and Santangelo (2022) rely on the indicators developed by Sostero et al. (2020) that are defined at a detailed level of occupations and based on the description of tasks performed in the corresponding occupations.

To analyse the impact of the COVID-19 pandemic, Chernoff and Warman (2023) develop a viral transmission risk (VTR) index and combine it with the routine task intensity index (RTI) of Autor et al. (2003) to characterize the workforce of the United States (U.S.) according to the two dimensions, *automation risk* and *infection risk* at the workplace. We apply these indicators to study the employment trends for different occupations during the COVID period, differentiated by their automation and viral transmission risk.

[1]Before the emergence of COVID-19, automation has already been identified as an important phenomenon that affects many occupations, see, for example, Frey and Osborne (2017), Arntz et al. (2017), and Abeliansky et al. (2020) for assessments of the extent to which future automation will impact employment.

[2]In addition to these characteristics, the authors also analyse the role of occupations being "critical" for the functioning of the economy, a categorisation that, however, was the result of political decisions.

The mentioned "automation push" works via different channels. First, in an attempt to avoid a forced shut-down of operations due to widespread workplace infections, firms may pre-emptively consider substituting machines for workers (*shielding incentive*). Second, as in any recession, the adjustment costs associated with investments in automation have gone down during the COVID-19 induced recession (*operational incentive*). Third, more frequent and repeated work absences of staff due to illness, as well as enduring health problems (such as the long-COVID syndrome) reduce the productivity of human labor relative to automated labor (Fischer et al., 2022). It is the last channel, which we will refer to as *productivity incentive* that this paper is interested in.

In line with Ding and Molina (2020), we expect that a potential automation push should be identifiable for occupations that are prone to automation, where the automation probability is a function of the tasks typically performed in the corresponding occupation (Autor et al., 2003; Frey and Osborne, 2017). Importantly, if the accelerated automation works via the productivity incentive, as we hypothesize, the automation push and the associated (medium-to-short term) employment effect should be asymmetric. More precisely, conditional on automatability, occupations that involve intensive social interaction and therefore carry a high viral infection risk, should be more affected. As a result, we should observe stronger declines in employment and in hours worked ("work volume") for occupations that can be replaced by machines and involve a viral infection risk. This impact of social interaction/viral transmission risk is a new element, in the sense that it started having economic impacts only with the onset of COVID-19. Korinek and Stiglitz (2021) refer to this new influence on the factor input decision of firms as extra shadow cost on physical interaction with humans (Broady et al., 2023). The bottom line is that COVID-19 altered the human-machine trade-off to the detriment of the former, thereby "forcing" automation. The extent to which individual occupations are affected by forced automation depends on whether the occupation is automatable, and if so, the degree of infection risk that it carries. Note that, from a theoretical perspective, the differentiated employment effects resulting from forced automation stems from a decline in the occupational labor demand for occupations with both high automation and high infection risk. In the empirical application, we have to rely on equilibrium outcomes for employment and hours worked, which are the result of demand and supply side factors.

Prettner and Stöllinger (2023) find that the strongest decline in employment during the COVID years (2020-2021) were registered for occupations that are characterized by high automatability and a high infection risk at the workplace. The same is true for hours worked, where the differentiated labor market outcomes are even more marked because the number of hours worked also include the adjustment at the intensive margin within occupations. Motivated by this descriptive evidence, we propose a theoretical model in which automatable labor and machines are perfect substitutes. Importantly, the implied human-machine trade-off is affected by the onset of COVID-19 (or more broadly, any pandemic), with the effect varying across occupations as a function of the degree of social interaction involved. This is consistent with the empirical evidence prior to the COVID-19 pandemic, where Houstecka et al. (2021) show that individuals who are employed are on average 35.5% more likely to be infected by the flu virus, with the likelihood increasing with a higher level of human contact at work. In addition, Pichler and Ziebarth (2017) utilize access of sick employees to paid sick-leave to show that less contact at work decreases contagion. Based on the theoretical considerations, we build an empirical model that features the infection risk at the workplace as a key variable. We are able to show that this infection risk reduces employment and hours worked during the pandemic for occupations with a high infection risk. As predicted by the theoretical model, this effect is detectable only for automatable jobs.

The contribution of this paper is twofold. First, we introduce a theoretical framework that can be used to study the employment-automation decision in a pandemic. Second, we are able to identify the negative effect of the shadow cost of human labor on employment and hours worked in Austria empirically. While we show this effect for the Austrian labor market, there are reasons to believe that this effect is equally present in other countries since the pandemic was a truly global phenomenon.[3]

The remainder of the paper is structured as follows. Section 2 presents the theoretical model. In Section 3, we describe the data in detail. Section 4 is devoted to testing the predictions of the model empirically. Finally, we conclude and draw policy recommendations in Section 5.

2 Infection risk and automation: theoretical considerations

We develop a model featuring a task-specific shadow cost of labor that alters the trade-off between human labor and machines in favor of the latter. The model set-up follows Krenz et al. (2021) in assuming that the economy produces final output according to the production function

$$Y_t = {H_t}^{1-\alpha} \sum_{\omega=1}^{J} x_{t,\omega}^{\alpha}, \tag{1}$$

[3]While the shadow cost of human labor must be expected to be comparable across countries, as long as the occupations have similar task structures, different labor market policy responses — notably the job retention schemes — are likely to have led to differences in the relative size of the effect on employment on the one hand and hours worked on the other hand.

where H is employment of high-skilled, non-automatable workers, x_ω is the amount of tasks ω used as an intermediate input in the production of final output, and α is the elasticity of final output with respect to the use of tasks. From the production function and the assumption of perfect competition, the wage rate of non-automatable workers, H_t, follows as

$$w_{t,H} = (1-\alpha)H^{-\alpha}\sum_{\omega=1}^{J} x_{t,\omega}^{\alpha} = (1-\alpha)\frac{Y_t}{H_t}. \tag{2}$$

As is well-known from the literature on endogenous economic growth (Romer, 1990; Jones, 1995), the inverse demand function for intermediate inputs, in our case tasks, follows as

$$pr_{t,\omega} = \alpha H_t^{1-\alpha} x_{t,\omega}^{\alpha-1}. \tag{3}$$

The production of tasks is performed with automatable labor services or with machines. Firms therefore face a production function of the form

$$x_{t,\omega} = \left[a_{t,l,\omega}(i_{t,l,\omega}) \cdot l_{t,\omega} + a_{t,p,\omega} \cdot p_{t,\omega}\right]^{\beta}, \tag{4}$$

where $l_{t,\omega}$ is employment of automatable workers at time t producing task ω. In the empirical application, these task-specific workers, for whom automation is technologically feasible, will be proxied by occupations. Furthermore, $a_{t,l,\omega}$ is the productivity of automatable workers at time t. Note that this productivity depends on the infection risk at the workplace, $i_{t,l,\omega} \in (0,1)$, which is the shadow cost of labor. Since the degree of social interaction (i.e., the viral infection risk) was economically irrelevant in the pre-COVID era, $i_{t,l,\omega}$ is 0 for all ω if $t < \tau$, where τ is the time point of the COVID-19 outbreak. For $t \geq \tau$, $i_{t,l,\omega}$ varies over tasks ω. Tasks ω are sorted such that the shadow cost of labor $i_{t,l,\omega}$ is increasing in ω so that $\partial i_{t,l,\omega}/\partial\omega > 0$. Next, $p_{t,\omega}$ is the amount of robots employed by the firm producing task ω at time t, with corresponding robot productivity being $a_{t,p,\omega}$.[4] For simplicity and in line with the literature on automation (Acemoglu and Restrepo, 2018, 2020), we assume that automatable labor used for producing task $l_{t,\omega}$ and robots, $p_{t,\omega}$, are perfect substitutes. Finally, β is the elasticity of task production with respect to automatable labor input.

[4]For a non-exhaustive list of recent contributions that analyze the effects of automation in terms of robots on various outcomes such as employment, inequality, and economic growth, see Acemoglu and Restrepo (2018, 2020); De Vries et al. (2020); Acemoglu and Restrepo (2022), Prettner and Strulik (2020), Hemous and Olsen (2022), and Abeliansky and Prettner (2023).

Task producing firms maximize their profits given by

$$\begin{aligned}\pi_{t,\omega} &= pr_{t,\omega}x_{t,\omega} - w_{t,l}l_{t,\omega} - \gamma r p_{t,\omega} \\ &= \alpha H_t^{1-\alpha}\left[a_{t,l,\omega}(i_{t,l,\omega}) \cdot l_{t,\omega} + a_{t,p,\omega} \cdot p_{t,\omega}\right]^{\alpha\beta} - w_{t,l}l_{t,\omega} - \gamma r p_{t,\omega}, \end{aligned} \tag{5}$$

where r is the capital rental rate and γ is the cost of one robot in terms of physical capital (Krenz et al., 2021). The productivity of robots differs across tasks, which reflects the ease with which the particular task can be automated. Given the variation in robot productivity and the variation in the shadow cost of labor, there will be a sorting of tasks. Producers will choose to employ robots instead of workers in tasks with comparatively high productivity of robots and a comparatively high shadow cost of labor (i.e., a high degree of infection risk at the workplace). By contrast, firms producing tasks with a comparatively low shadow cost of labor and a low level of technological feasibility of automation will prefer to employ workers instead of robots.

Thus, there will be a threshold level of the relation between the infection risk and the technological feasibility of automation at which a firm is indifferent between employing workers or robots. Below the threshold, a firm will employ workers and above the threshold, a firm will employ robots. Profit maximization implies the following first-order conditions

$$\frac{\partial \pi_{t,\omega}}{\partial l_{t,\omega}} = \alpha^2\beta H_t^{1-\alpha}\left[a_{t,l,\omega}(i_{t,l,\omega}) \cdot l_{t,\omega} + a_{t,p,\omega} \cdot p_{t,\omega}\right]^{\alpha\beta-1} a_{t,l,\omega}(i_{t,l,\omega}) - w_{t,l} \stackrel{!}{=} 0, \tag{6}$$

$$\frac{\partial \pi_{t,\omega}}{\partial p_{t,\omega}} = \alpha^2\beta H_t^{1-\alpha}\left[a_{t,l,\omega}(i_{t,l,\omega}) \cdot l_{t,\omega} + a_{t,p,\omega} \cdot p_{t,\omega}\right]^{\alpha\beta-1} a_{t,p,\omega} - \gamma r \stackrel{!}{=} 0. \tag{7}$$

From (6) and acknowledging that $p_{t,\omega} = 0$ for firms that produce with humans, we derive employment of low-skilled workers as

$$l_{t,\omega} = \left[\frac{w_{t,l}}{a_{t,l,\omega}(i_{t,l,\omega})\alpha^2\beta H_t^{1-\alpha}}\right]^{\frac{1}{\alpha\beta-1}} \cdot \frac{1}{a_{t,l,\omega}(i_{t,l,\omega})}. \tag{8}$$

From (7) and acknowledging that $l_{t,\omega} = 0$ for firms that produce fully automated at time t, employment of robots follows as

$$p_{t,\omega} = \left[\frac{\gamma r}{\alpha^2\beta H^{1-\alpha}a_{p,\omega}}\right]^{\frac{1}{\alpha\beta-1}} \cdot \frac{1}{a_{p,\omega}}. \tag{9}$$

Plugging these results back into the expression for profits (5) and setting the other production factor equal to zero yields profits of firms that produce with workers ($\pi_{t,\omega,l}$) as

$$\pi_{t,\omega,l} = (1-\alpha\beta)\alpha H_t^{1-\alpha}\left[\frac{w_{t,l}}{a_{t,l,\omega}(i_{t,l,\omega})\alpha^2\beta H_t^{1-\alpha}}\right]^{\frac{\alpha\beta}{\alpha\beta-1}} \tag{10}$$

and profits of firms that produce with robots ($\pi_{t,\omega,p}$) as

$$\pi_{t,\omega,p} = (1-\alpha\beta)\alpha H^{1-\alpha}\left[\frac{\gamma r}{\alpha^2\beta H^{1-\alpha}a_{p,\omega}}\right]^{\frac{\alpha\beta}{\alpha\beta-1}}. \tag{11}$$

The threshold level of the ratio of productivity of workers versus robots below which firms would produce with robots and above which firms would produce with human workers is obtained by setting the profits of firms that only produce with workers equal to the profits of firms that only produce with robots. After some reformulations, we arrive at

$$\frac{a_{t,l,\omega}(i_{t,l,\omega})}{a_{t,p,\omega}} = \frac{w_{t,l}}{\gamma r}. \tag{12}$$

This expression has a very intuitive interpretation: The left-hand side is the ratio between the productivity of human workers and robots, while the right-hand side is the ratio between the price of human labor and the price of robots. If, ceteris paribus, the wage rate is higher, the threshold productivity level above which firms produce with human labor will be higher. If, by contrast, the interest rate (r) or the capital input requirement for robots (γ) are higher, the threshold productivity level above which firms produce with human labor will be lower (cf. Krenz et al., 2021). In addition, the left-hand side of equation (12) shows that the threshold is jointly determined by the relative productivity of labor versus robots and the shadow cost of human labor, $i_{t,l,\omega}$, as determined by the infection risk at the workplace. In the empirical investigation, we focus on the impact of this shadow cost because it is exactly this factor that changed during the COVID period, while it was essentially zero before COVID.

3 Data description

The data used in this study was retrieved from the Austrian microcensus (*Mikrozensus-Arbeitskräfteerhebung*) for the period 2015-2021. This source provides internationally comparable employment and housing statistics for the Austrian economy, and includes information on relevant labor market indicators (e.g., unemployment) as well as socio-demographic ones (e.g., education). It includes information from about 22,500 (randomly selected) households in Austria on a quarterly basis.

The main variables we use from the survey are the number of persons employed and the total number of annual hours worked (i.e., "work volume" or *Arbeitsvolumen*). Following the definition from the International Labour Organisation (ILO), employed individuals include employees and self-employed people. In addition, those who receive child-care allowance and those on parental leave pay are also included. We follow the methodology of Statistik Austria (2019) and calculate the work volume (hours worked) using the actual hours worked during the week of the interview in both primary and secondary occupations of persons employed. To get the annual work volume, the actual hours worked per week were multiplied by 52. It should be noted that employment aggregates at any level of aggregation (e.g., by occupation or by gender) are retrieved using the weighting factor for each person in the sample.

The microcensus contains a wide range of individual data, especially a large set of socio-economic characteristics. Of importance are the occupations (minor groups)[5] because automation risk and viral transmission risk vary across occupations. The industry affiliation is also important (industry groups).[6] We also make use of the information of the region in which persons work, which is provided at the NUTS-2 level, corresponding to the *Bundesländer* in Austria.

In addition, we differentiate the employment and work volume by demographic characteristics, notably gender, age, and educational attainment. The educational attainment follows the International Standard Classification of Education (ISCED) and we aggregate ISCED categories 1 and 2 to a low-skilled group, ISCED categories 3 and 4 to a medium-skilled group and ISCED categories 4 or higher to a high-skilled group. We also build four age cohorts comprising those aged 15-24, 26-49, 50-64, and those older than 65 years. Finally, we combine the Austrian employment data with the RTI and VTR indices described in Section 1.[7] The underlying information for these indices comes from the U.S. O*NET repository.[8]

[5]Minor groups are occupations as reported in the International Classification of Occupations 2008 (ISCO-08) at the 3-digit level comprising 130 occupations.

[6]Industries are reported according to the Statistical Classification of Economic Activities in the European Community, Revision 2, or NACE Rev. 2 for short. The data are available up to the level of NACE industry groups (3-digit level).

[7]An in-depth description and discussion of the indices is provided in Section 4.1 and in the Appendx.

[8]The O*NET is a publicly available electronic list of all existing occupations in the United States, recorded at the Standard Occupational Classification (SOC) System. It contains a large set of variables that describe work and worker characteristics in each occupation. Of the numerous worker and job-oriented data categories, the relevant one for calculating the RTI index and the VTR index are (i) work activities, (ii) abilities, and (iii) work contexts. We combine the scores of the selected "tasks" within

Table 1: Summary statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
(ln) Working hours	164,878	11.9396	1.1506	3.5795	16.6319
(ln) Employment	171,812	4.6028	0.9715	1.5644	9.4044
Age	171,812	2.1419	0.8019	1	4
Skill	171,812	2.2112	0.6843	1	3
Gender	171,812	1.5717	0.4948	1	2
RTI	171,812	0.5470	0.2043	0	1
VTR	171,812	0.3976	0.1372	0.0769	0.9667

Notes: Statistics for ISCO 1-digit occupations, NACE Rev.2 1-digit industries and NUTS-2 regions are not included since they are categorical variables with no "quantitative" interpretation.

Table 1 below shows the summary statistics of the variables used in the empirical investigation. Although the standard deviation of the first two variables is not so large in terms of the mean according to the values from the table it should be kept in mind that these values are in log form. When these are converted to their level equivalents, the standard deviation becomes a larger share of the mean. In terms of age, the largest group is that of workers between 25 and 49 years old (group 2). The mean is larger than 2 given that the two higher groups (those between 50 and 64 and 65 and above represent a larger share than those between 15 and 24 years of age). With respect to the skill level, there are more individuals in "high-skilled" jobs (with assigned value 3) than in "low-skilled" jobs (with assigned value 1) because the mean is also larger than 2. The largest group, however, is the "medium-skilled" group (with assigned value 2). The mean of the RTI is around 0.55 but there seems to be some dispersion as indicated by the standard deviation. Finally, regarding the gender, there are more males in the sample than females because the mean is higher than 1.5.

4 Empirical model and results

4.1 Model specification

In this section, we aim to test the model predictions — namely the relevance of the productivity incentive for accelerating automation in the advent of a pandemic. To this end, we associate the shadow cost of human labor, $(i_{t,l,\omega})$, which governs the allocation

these broader categories to the indices and sub-indices as described in Prettner and Stoellinger (2023).

decision for producing tasks, with the viral transmission index (VTR) of Chernoff and Warman (2023) (including the adjustments introduced in Prettner and Stoellinger, 2023) in combination with a dummy variable for the COVID years (2020 and 2021). As seen in Table 1 above, the VTR ranges from 0 to 1 and reflects the degree of viral transmission risk at the workplace of occupational groups.[9]

With the general logic of a difference-in-difference in mind, we argue that we can identify the shadow cost of labor with an interaction between the VTR and the dummy for the COVID period and study its impact on Austrian employment (and hours worked) at the occuaptional level. We therefore consider occupations as the empirical counterpart of the automatable labor used in the production of tasks. The rationale for using this interaction term as indicator for the shadow cost is the following. In pre-COVID years, the shadow cost of labor was zero for all occupations. From 2020 onward, the occupation-specific shadow cost is taken into account by firms when making their decision of whether producing tasks with (automatable) human labor or with machines. This shadow cost is higher if the viral infection risk, as measured by the VTR, is higher. Irrespective of any pre-COVID-19 relationship between the VTR and employment, which is likely in view of the structural developments towards a service economy (that features more occupations with a high VTR), any additional effect of the COVID dummy variable for occupations with a high VTR value can be assigned to the shadow cost of labor.[10] Important for our line of reasoning is that we should not be able to detect a similar effect of the interaction term for non-automatable occupations.

The labor market outcomes of interest are employment and the number of hours worked, which are used alternatively as depended variables. Among the numerous dimensions of the employment data, the most important dimension is occupations for two reasons. First, they are directly related to the theoretical model. Second, the variation in the VTR (our main variable of interest) and in the RTI comes from occupations.[11]

Employed labor at time t, $N_t \in (number\ of\ persons\ employed,\ hours\ worked)$, is divided into automatable labor, which we denote as L_t, and non-automatable labor,

[9] In principle, the values of the VTR range from 0 to 1 across all occupations because the values were standardized. However, the standardisation was made at the level of 4-digit ISCO occupations. When aggregating the occupations from the 4-digit to the 3-digit ISCO level, the maximum is below 1 if the resulting top 3-digit occupation contains more than one 4-digit occupations. This is the case in the VTR but not in the case of the RTI.

[10] Implicitly we assume that variations in the employment level of occupations with a high VTR that are explained by the COVID-dummy, result from changes in the demand for labor for these occupations.

[11] The VTR and the RTI have no variation over time, because the underlying information on tasks for the occupations in the O*NET repository is updated in irregular intervals. More precisely, the updates are regular but each update only covers a subset of occupations, which makes it difficult to trace the task structure of individual occupations.

H_t, with $N_t = L_t + H_t$. For the distinction between the two groups of occupations, we use the routine-task intensity index of Autor et al. (2003) in the version described in Acemoglu and Autor (2011). In line with Chernoff and Warman (2023), we interpret occupations as automatable when the RTI index is above 0.5 and as non-automatable otherwise. We are mainly interested in the effect of the shadow cost of human labor of automatable occupations, $i_{l,t,\omega}$, which is economically relevant only in the COVID years. The restriction to automatable occupations (in the main specification) is due to the fact that the productivity incentive should only lead to an accelerated substitution of human labor by machines for occupations where this is possible. Empirically, we proxy the shadow cost of human labor by the VTR and interact it with an indicator variable for the COVID period. Hence, we estimate the following empirical specification

$$\begin{aligned} L_{g,s,a,\omega,j,r,t} &= \alpha + \beta_1 \cdot VTR_\omega + \gamma \cdot (VTR_\omega \cdot COVID) + \beta_2 \cdot COVID + \beta_3 \cdot RTI_\omega + \\ &\quad + gender_g + skill_s + age_a + occ_\Omega + ind_j + region_r + \epsilon_{g,s,a,\omega,j,r,t}, \end{aligned} \tag{13}$$

where gender, educational attainment (or skill for short), and age are indicator variables with the corresponding indices g, s, and a. Furthermore, we include indicator variables for industries (j), for regions (r), and for occupations (ω). The indicator variables for occupations are at the level of major groups (ISCO-1-digit occupations), while the employment data are available at the level of minor groups (ISCO-3-digit occupations). This is why the subscript of the VTR and the RTI (in both cases ω) differs from that of the indicator variable for occupations (Ω). Note again, that the VTR and the RTI variable do not vary over time but only over occupations.[12] Equally important is the variable COVID, which is a time dummy taking the value 1 for the years 2020 and 2021, and zero otherwise. The COVID dummy is essential because it belongs to the interaction term $VTR \cdot COVID$, which allows us to estimate the effect of the shadow cost of labor on labor demand — and consequently on employment and hours worked — in the advent of the pandemic. If the viral transmission risk led to a push for robot adoption — as we hypothesize — then employment and the number of hours worked in automatable occupation ω should be affected negatively. The extent to which occupation ω is affected by the pandemic-induced automation push depends on its VTR.

Note that the main effect of the VTR alone is not indicative of the shadow cost of human labor. It rather captures the overall employment trends of occupations that involve

[12] The lack of time variation of the VTR and the RTI is the reason why we do not refer to the indicator variables that capture the richness of variation in the employment variables as fixed effects but as indicator variables.

more or less social interaction (and their associated viral transmission risk). Notably, employment in occupations with a high degree of social interaction was increasing over the last decade for several reasons that are unrelated to the viral transmission risk.[13] Firstly, most occupations with high social interaction have a lower risk of being automated. A second reason is the structural shift of the Austrian economy towards services, which also increased the demand for labor with more social interaction.

Overall, the COVID-19 dummy allows identifying the effect of the shadow cost of human labor on employment and hours worked in the following way. On average, occupations with a high VTR experienced an increase in labor demand. This may even be the case for the pandemic years. However, since the pandemic, the VTR also imposes a shadow cost, which reduces demand for labor. Thus, we can identify the effect of the shadow cost on labor demand and the resulting employment with the coefficient γ of the interaction term between the VTR and the COVID variable. More precisely, we expect γ to be negative for the sub-sample of automatable jobs, L_t, which is the dependent variable in the main regression in Equation (13). Moreover, when the sample is restricted to automatable occupations, we still control for the RTI. Since the RTI is indicative of the ease with which occupations can be automated, we expect a negative sign for the corresponding coefficient β_2.[14]

4.2 Empirical results

The estimates from our empirical model are presented in Table 2 for both employment and hours worked. The main results are those in columns (1) and (4), which includes the interaction term $VTR \cdot COVID$ for the sample of automatable occupations, that is, those occupations for which the shadow cost of labor (potentially) exerts an economic impact from 2020 onward.

In line with our central hypothesis, we find that the coefficient of the interaction term is negative and statistically significant. The main effect of the VTR is positive, but only marginally significant. Nevertheless, this positive effect is also expected due to the structural developments mentioned earlier. Furthermore, the estimate for the RTI is negative, suggesting that the higher the RTI, the lower is, *ceteris paribus*, the (occupation-industry-level) employment of labor. We observe that, on average, those with medium skills exhibit higher employment than those with low skills. In addition, those aged between 25 and 49 are also exhibiting more employment than those in the reference

[13]Once more this effect can be supposed to come primarily from changes in firms' labor demand.

[14]We show in the appendix that the exclusion of the RTI variable does not change the results.

Table 2: COVID-related shadow cost of labor and labor market outcomes

Dependent variable:	Employment (log)			Work volume (log)		
Sample:	Automatable occupations	Non automatable occupations	All occupations	Automatable occupations	Non automatable occupations	All occupations
	(1)	(2)	(3)	(4)	(5)	(6)
Female workers	0.0155	-0.0123	-0.0025	-0.2142***	-0.2405***	-0.2408***
	(0.0409)	(0.0280)	(0.0314)	(0.0405)	(0.0259)	(0.0286)
Medium-skill	0.1597**	0.2102***	0.1631***	0.1635**	0.2505***	0.1738**
	(0.0556)	(0.0238)	(0.0439)	(0.0645)	(0.0379)	(0.0519)
High-skill	0.0362	0.2019*	0.1004	0.0352	0.2767**	0.1243
	(0.0747)	(0.0875)	(0.0683)	(0.0890)	(0.1006)	(0.0838)
Age 25-49	0.1300***	0.1148**	0.1189***	0.1569**	0.2036***	0.1713***
	(0.0317)	(0.0358)	(0.0278)	(0.0526)	(0.0542)	(0.0433)
Age 50-64	-0.0382	-0.0389	-0.0408	-0.0525	0.0418	-0.0154
	(0.0429)	(0.0470)	(0.0359)	(0.0506)	(0.0686)	(0.0482)
Age 65 +	-0.4841***	-0.4610***	-0.4547***	-1.4997***	-1.2005***	-1.3265***
	(0.0441)	(0.0683)	(0.0423)	(0.0627)	(0.1156)	(0.0911)
RTI	-0.3856**	-0.1330	-0.1431	-0.5919***	-0.1219	-0.1829
	(0.1313)	(0.1282)	(0.0944)	(0.0935)	(0.2098)	(0.1394)
VTR	0.5726*	0.3205***	0.4102**	0.4733*	0.3840**	0.4031*
	(0.2756)	(0.0793)	(0.1305)	(0.2154)	(0.1300)	(0.1879)
VTR x COVID	-0.0772**	0.0596	0.0296	-0.1513***	0.0447	-0.0032
	(0.0214)	(0.0661)	(0.0357)	(0.0390)	(0.1062)	(0.0573)
COVID	0.0207***	-0.0188	-0.0155	-0.0138	-0.0811*	-0.0676**
	(0.0051)	(0.0292)	(0.0157)	(0.0145)	(0.0359)	(0.0208)
Constant	4.4865***	4.3568***	4.3799***	12.1105***	11.7234***	11.8428***
	(0.1808)	(0.1009)	(0.0835)	(0.1347)	(0.1830)	(0.1465)
Industry FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	96,671	75,141	171,812	92,693	72,185	164,878
R-sq.	0.3515	0.3472	0.3326	0.3279	0.3049	0.3017

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Two-way standard errors clustered at the level of ISCO-1-digit occupations and years in parenthesis.

category (between 15 and 24 years of age), while those above the official retirement age work less in relative terms to those in the reference category.

The second column contains a "placebo" specification. This specification is identical to the one from models (1) and (4), but estimates the effect for the sample of non-automatable occupations. In this placebo regression — as expected — the RTI variable is not statistically significant[15] and, even more important, the coefficient of the interaction term $VTR \cdot COVID$ is not statistically significant either. This is to be expected because — even if there was a productivity incentive — non-automatable jobs simply cannot be replaced by machines.

The third column presents the results for the entire sample. These are more similar to those for the placebo regressions, which cannot be explained with the number of observations. Rather, it seems that the employment effect of the shadow cost is specific to the automatable occupations, exactly as predicted in the theoretical model.

The second set of results (columns 4-6) repeats the empirical exercise using hours worked (*work volume*) instead of employment as the dependent variable. The difference is that hours worked also captures the within-occupation margin of the adjustment in labor demand and resulting employment. This within-occupation margin is important because in view of the generous job retention scheme in Austria (*Kurzarbeitsregelung*), the reduction in labor demand on the side of firms took primarily the form of reducing working hours. Most European countries, including Austria, implemented job retention schemes during the COVID-inflicted recession. This differs to the U.S., which opted for extending unemployment benefits. Consequently, the different labor market policy responses to the COVID-inflicted recession explain why the unemployment figures went up much stronger in the U.S. than in the EU. Therefore, we expect to see in Austria a larger effect of the shadow price of labor for hours worked than for employment (-0.077). Indeed, with -0.151, the magnitude of the coefficient of the interaction term in the model with hours worked as the dependent variable is about twice as large as in the employment model. Qualitatively, the results of the two sets of models (for hours worked and for employment) are fully aligned. The only difference worth mentioning is that the coefficient for gender (a variable takes takes the value of 1 for female workers), is negative in the model for hours worked. This can be explained by the fact that female workers

[15]The lack of explanatory power of the RTI for what we have defined as non-automatable occupations is not a necessary outcome. Rather, it confirms the appropriateness of our threshold for distinguishing automatable from non-automatable occupations that we had set to 0.5 following Chernoff and Warman (2023). If the RTI had an impact on employment (hours worked) in this group, this would suggest that we had chosen an inappropriate threshold value. Fortunately, this is not the case so that we interpret the insignificant coefficient for the RTI in the placebo regression as confirmation for our sample split.

reduced working hours more strongly than their male counterparts. One explanation for this pattern is that women seem to work in industries and regions where short-term work was more prevalent, another is that in view of the need for home schooling and other household-related obligations, women reduced — or were forced to reduce — working hours more strongly.

In the Appendix, we provide some robustness analyses, where we remove the RTI index (Table 5), trim the data to remove those observations with the highest/lowest values of the RTI index (Table 6), use a three-way clustering approach instead of a two-way clustering approach (7), and we change the VTR index, that is, we use the original VTR index as developed by Chernoff and Warman (2023) (8). Results remain unchanged.

We finish the discussion of the results by looking at the marginal effects of the COVID-period on employment and hours worked. As indicated by the negative coefficient of the interaction term in our regression model, the magnitude of the effect on labor market outcomes of automatable occupations depends on the VTR index. Figure 1 shows the marginal effects of the COVID-dummy on employment and hours worked, respectively, for occupations with different levels of social interaction/viral transmission risk.

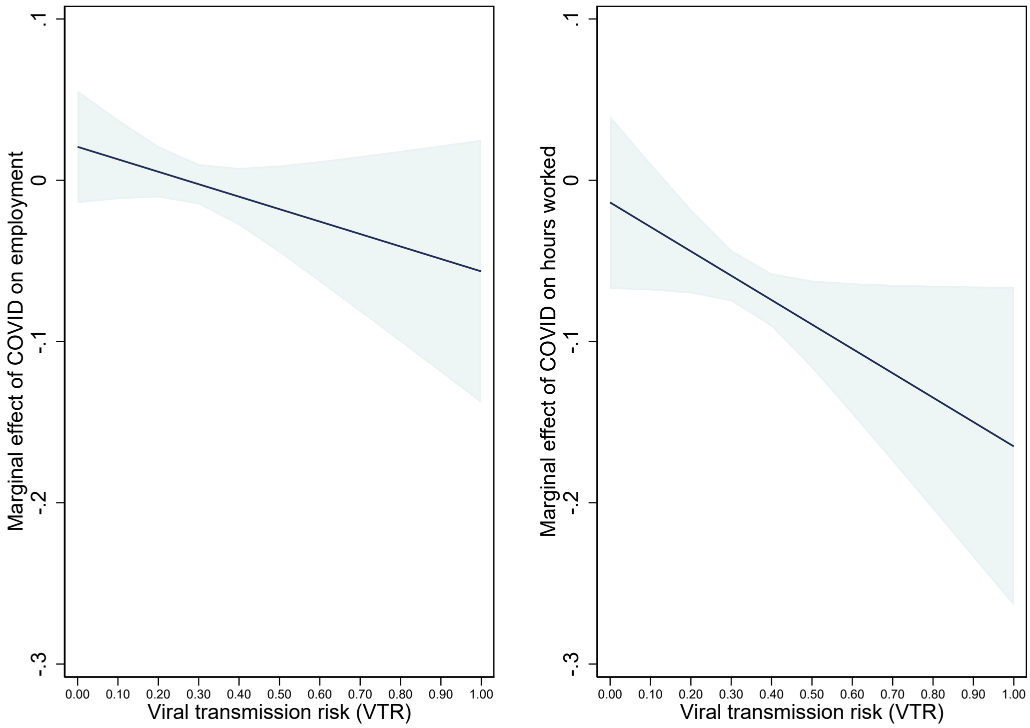

Figure 1: Marginal effects of COVID on labor market outcomes

Source: Regressions in column 1 and column 4 in Table 2.
Note: The sample only includes automatable occupations.

The marginal effects visualize the fact that the impact on hours worked in Austria was much stronger than that on employment. Also, the point estimate of the employment effect is positive for occupations with very low VTR values. This is not the case for the point estimate of the effect on hours worked, which is always negative. Evaluated at the mean VTR value, 0.39, the marginal effect of the COVID-period on hours worked is -0.072[16], while for occupations with the maximum value of 1, the effect is -0.165. Note that this is exactly the pattern expected from the shadow cost of labor stemming from the infection risk.

[16]For occupations with a VTR of 0.39, the COVID-years lead to a reduction in hours worked of 7.2%.

5 Conclusions

A theoretical model of production based on human labor and automation technologies shows that firms are more prone to automating occupations that are associated with a greater infection risk in times of rapidly spreading infectious diseases such as in pandemics. We test this theoretical prediction using Austrian microcensus data on the routine task intensity of different occupations as a proxy for technological automatability and the viral transmission risk of an occupation as a proxy for the susceptibility of this occupation during times of pandemics. Controlling for other important aspects that affect employment (such as gender, age, and the skill level), we show that infection risk at work in times of pandemics indeed reduces employment but only for automatable occupations. Thus, the theoretical implications are supported by the available empirical evidence.

Our results show that occupations that are susceptible to viral transmission and to automation face a particularly grim situation in times of a pandemic. While occupations that are difficult to automate could benefit through job retention schemes ("Kurzarbeit" in German speaking countries) in times of a pandemic, occupations that are susceptible to automation may face permanent employment reductions. This has consequences for the optimal policy response because investing in retraining a worker whose job is susceptible to automation and viral transmission may be a better option during a pandemic than to put these workers on a furlough scheme. For workers that are not susceptible to automation, however, the opposite is likely to hold true.

Throughout this paper we discussed the effects of viral transmission through social interaction in the context of the COVID-19 pandemic. However, the mechanism and the empirical results remain relevant and may even become more prevalent in the future. The reason is that growing urbanisation, an increasing level of international integration, and humans expanding into natural habitats with pathogens against which they do not yet have an acquired immunity (e.g., deforestation in Brazil) all increase the probability of an outbreak of another pandemic, or the likelihood with which infections spread (Marani et al., 2021; Bloom et al., 2022). In addition, the relevance is not only restricted to health crises because the productivity effect may also kick in in a number of other scenarios. For example, one could think of societies reaching a degree of polarisation such that the gathering of a larger group of workers may result in regular disputes and conflicts at the workplace which would, just like health issues, also reduce labor productivity. Many more scenarios are imaginable though chances are that the next event increasing the shadow cost of labor will (as with COVID-19) be an entirely unexpected one.

Future research avenues include extending the analysis to see whether the results we have found also hold for other countries and whether they depend on the underlying policy response to pandemics such as COVID-19.

Acknowledgements

We would like to thank Gizem Akar for valuable comments and discussions and Iris Butzlaff from the Austrian Social Science Data Archive (AUSSDA) for granting access to and the continued support in the use of the Austrian microcensus data. Klaus Prettner is grateful to the Austrian National Bank (OeNB) for the funding of the project "The Viral Transmission Risk of Occupations in Austria and Its Implications for Automatability (TROIA)" through the Jubiläumsfonds (project number: 18754). The OeNB had no role in the study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication.

Declarations of interest: none.

Appendix

5.1 Appendix 1: Definition of the RTI and VTR indices

The routine-task intensity (RTI) index is composed of 16 O*NET variables, which are grouped into five sub-indices: non-routine analytical cognitive (NRA), non-routine interpersonal cognitive (NRI), non-routine manual (NRM), routine cognitive (RC), and routine manual (RM) tasks. The relevant variables and their origin in the O*NET database are listed in Table 3.

Table 3: Definition of the RTI index

Sub-Index and variables therein	Category in O*NET
Routine cognitive tasks (RC)	
Importance of Repeating Same Tasks	Work Context
Importance of Being Exact or Accurate	Work Context
Structured versus Unstructured Work	Work Context
Routine manual (RM)	
Pace Determined by Speed of Equipment	Work Context
Spend Time Making Repetitive Motions	Work Context
Controlling Machines and Processes	Work Activities
Non-routine-analytical (NRA)	
Analyzing Data or Information	Work Activities
Thinking Creatively	Work Activities
Interpreting the Meaning of Information for Others	Work Activities
Non-routine-cognitive (NRC)	
Establishing and Maintaining Interpersonal Relationships	Work Activities
Guiding, Directing, and Motivating Subordinates	Work Activities
Coaching and Developing Others	Work Activities
Non-routine-manual (NRM)	
Operating Vehicles, Mechanized Devices, or Equipment	Work Activities
Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	Work Context
Manual Dexterity	Abilities
Spatial Orientation	Abilities

Source: O*NET version 24.3; authors' own calculations following the definition of the RTI in Autor et al. (2003).

The construction of the VTR index is less complex in the sense that it does not consist of sub-indices but simply of five variables (or seven variables in the case if the adjusted VTR which is used for the main specifications). All variables originate from the category "Work Context" and the category "Work Activities" within the O*NET repository. The relevant variables are listed in Table 4.

Table 4: Definition of the VTR index

Variables defining the VTR	**Category in O*NET**
Physical proximity	Work Context
Face-to-Face Discussions	Work Context
Exposed to Disease or Infections	Work Context
Outdoors, Exposed to Weather	Work Context
Outdoors, Under Cover	Work Context
Performing for or Working Directly with the Public	Work Activities*
Assisting and Caring for Others	Work Activities*

Source: O*NET version 24.3; authors' own calculations based on the definition of the VTR in Chernoff and Warman (2023).
Note: The variables marked by an asterisk are additional variables added by Prettner and Stoellinger (2023)

5.2 Appendix 2: Additional empirical results (robustness checks)

Appendix Table 5 reports the same results as Table 2 in the main text, only that it omits the RTI as a control variable. Apart from that, the model is identical and Appendix Table 5 show that none of the results are sensitive towards the inclusion or exclusion of the RTI as a control variable. The same conclusions can be drawn when we trim the data to remove those observations that lie beneath/above the 5th and 95th percentile of the RTI distribution, respectively (Appendix Table 6). In addition, the same holds when we use an alternative way to calculate the standard errors and use a three-way cluster approach, namely, we cluster by year, NACE 2-digit industries, and ISCO 1-digit occupations.

We also report results for the original VTR index developed by Chernoff and Warman (2023). As mentioned in Section 4.1, we use an adjusted VTR index stemming from Prettner and Stoellinger (2023). This adjusted VTR includes two more variables from the US O*NET database, which are "Performing for or Working Directly with the Public" and "Assisting and Caring for Others", both stemming from the category of work activities. The motivation for including these two variables is to reflect even more strongly than in the original Chernoff-Warman-Index the tight relationship between social interaction and the viral infection risk.

The results in Appendix Table 8 replicate the main results in the paper using the original index. The results are the same as reported in Table 2 in the main text. The additional results with the original VTR, which we refer to as alternative index, illustrate that the refinement of the VTR is not driving the results reported in the main text (in Table 2).

Table 5: COVID-related shadow cost of labor and labor market outcomes, alternative specification

Dependent variable:	Employment (log)			Work volume (log)		
Sample:	Automatable occupations	Non automatable occupations	All occupations	Automatable occupations	Non automatable occupations	All occupations
	(1)	(2)	(3)	(4)	(5)	(6)
Female workers	0.0013	-0.0114	-0.0073	-0.2361***	-0.2397***	-0.2470***
	(0.0398)	(0.0286)	(0.0292)	(0.0380)	(0.0250)	(0.0257)
Medium-skill	0.1572**	0.2104***	0.1633***	0.1596**	0.2507***	0.1741**
	(0.0555)	(0.0238)	(0.0438)	(0.0639)	(0.0381)	(0.0519)
High-skill	0.0336	0.2019*	0.1009	0.0313	0.2768**	0.1251
	(0.0746)	(0.0865)	(0.0682)	(0.0887)	(0.1007)	(0.0836)
Age 25-49	0.1306***	0.1150**	0.1191***	0.1578**	0.2038***	0.1715***
	(0.0323)	(0.0358)	(0.0277)	(0.0531)	(0.0540)	(0.0430)
Age 50-64	-0.0377	-0.0383	-0.0408	-0.0518	0.0423	-0.0154
	(0.0437)	(0.0470)	(0.0362)	(0.0514)	(0.0682)	(0.0482)
Age 65 or more	-0.4825***	-0.4592***	-0.4530***	-1.4977***	-1.1989***	-1.3244***
	(0.0435)	(0.0692)	(0.0425)	(0.0615)	(0.1148)	(0.0893)
VTR	0.6231*	0.3379***	0.4560**	0.5504	0.3999**	0.4614**
	(0.3143)	(0.0780)	(0.1314)	(0.2851)	(0.1128)	(0.1660)
VTR x COVID	-0.0803***	0.0575	0.0235	-0.1548***	0.0430	-0.0108
	(0.0185)	(0.0483)	(0.0396)	(0.0348)	(0.0925)	(0.0692)
COVID	0.0229***	-0.0181	-0.0127	-0.0107	-0.0804**	-0.0641**
	(0.0053)	(0.0224)	(0.0177)	(0.0143)	(0.0317)	(0.0252)
Constant	4.2066***	4.3017***	4.2850***	11.6811***	11.6729***	11.7215***
	(0.1244)	(0.0700)	(0.0578)	(0.1144)	(0.1092)	(0.0854)
Industry FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	96,671	75,141	171,812	92,693	72,185	164,878
R-sq.	0.3504	0.3471	0.3323	0.3262	0.3049	0.3014

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Two-way standard errors clustered at the level of ISCO-1-digit occupations and years in parenthesis.

As with the results in the main text, the coefficient of the interaction term $VTR \cdot COVID$ is negative and statistically significant only for the automatable occupations. Moreover, the magnitude of the coefficients are very similar in the two variants of the model. This is true for the model featuring employment as the dependent variable as well as that featuring hours worked.

Table 6: COVID-related shadow cost of labor and labor market outcomes, trimmed data (RTI)

Dependent variable:	Employment (log)			Work volume (log)		
Sample:	Automatable occupations	Non automatable occupations	All occupations	Automatable occupations	Non automatable occupations	All occupations
	(1)	(2)	(3)	(4)	(5)	(6)
Female workers	0.0142	-0.0117	-0.00352	-0.214***	-0.249***	-0.242***
	(0.0423)	(0.0362)	(0.0344)	(0.0413)	(0.0324)	(0.0313)
Medium-skill	0.164**	0.221***	0.169***	0.170**	0.265***	0.183**
	(0.0588)	(0.0250)	(0.0453)	(0.0681)	(0.0371)	(0.0534)
High-skill	0.0334	0.159*	0.0784	0.0351	0.227**	0.0997
	(0.0780)	(0.0694)	(0.0632)	(0.0926)	(0.0811)	(0.0774)
Age 25-49	0.133***	0.108**	0.118***	0.159**	0.184**	0.164***
	(0.0329)	(0.0351)	(0.0293)	(0.0509)	(0.0511)	(0.0416)
Age 50-64	-0.0364	-0.0509	-0.0447	-0.0493	0.00972	-0.0280
	(0.0442)	(0.0498)	(0.0383)	(0.0493)	(0.0662)	(0.0450)
Age 65 or more	-0.487***	-0.460***	-0.453***	-1.488***	-1.217***	-1.329***
	(0.0452)	(0.0810)	(0.0486)	(0.0633)	(0.126)	(0.0915)
RTI	-0.432*	-0.0186	-0.0883	-0.650***	-0.319	-0.177
	(0.191)	(0.207)	(0.0804)	(0.123)	(0.213)	(0.117)
VTR	0.566*	0.321***	0.424**	0.480*	0.333**	0.413*
	(0.274)	(0.0821)	(0.140)	(0.216)	(0.121)	(0.189)
VTR x COVID	-0.0636**	0.0655	0.0387	-0.146**	0.0381	-0.00571
	(0.0220)	(0.0892)	(0.0364)	(0.0428)	(0.107)	(0.0465)
COVID	0.0169*	-0.0157	-0.0167	-0.0168	-0.0755*	-0.0671***
	(0.00787)	(0.0363)	(0.0160)	(0.0162)	(0.0341)	(0.0174)
Constant	4.521***	4.337***	4.354***	12.15***	11.87***	11.85***
	(0.204)	(0.0789)	(0.0798)	(0.143)	(0.125)	(0.122)
Industry FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	91,128	65,455	156,583	87,394	62,888	150,282
R-sq.	0.351	0.351	0.333	0.329	0.313	0.305

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Two-way standard errors clustered at the level of ISCO-1-digit occupations and years in parenthesis.

Table 7: COVID-related shadow cost of labor and labor market outcomes, alternative clustering

Dependent variable:	Employment (log)			Work volume (log)		
Sample:	Automatable occupations	Non automatable occupations	All occupations	Automatable occupations	Non automatable occupations	All occupations
	(1)	(2)	(3)	(4)	(5)	(6)
Female workers	0.0155	-0.0123	-0.00249	-0.214***	-0.240***	-0.241***
	(0.0454)	(0.0341)	(0.0347)	(0.0470)	(0.0320)	(0.0328)
Medium-skill	0.160**	0.210***	0.163***	0.163**	0.251***	0.174**
	(0.0534)	(0.0266)	(0.0430)	(0.0623)	(0.0414)	(0.0510)
High-skill	0.0362	0.202*	0.100	0.0352	0.277**	0.124
	(0.0745)	(0.0891)	(0.0687)	(0.0901)	(0.102)	(0.0842)
Age 25-49	0.130***	0.115**	0.119***	0.157**	0.204**	0.171***
	(0.0311)	(0.0376)	(0.0287)	(0.0523)	(0.0553)	(0.0445)
Age 50-64	-0.0382	-0.0389	-0.0408	-0.0525	0.0418	-0.0154
	(0.0442)	(0.0505)	(0.0394)	(0.0520)	(0.0718)	(0.0522)
Age 65 or more	-0.484***	-0.461***	-0.455***	-1.500***	-1.200***	-1.326***
	(0.0466)	(0.0695)	(0.0487)	(0.0565)	(0.120)	(0.0967)
RTI	-0.386*	-0.133	-0.143	-0.592**	-0.122	-0.183
	(0.192)	(0.217)	(0.113)	(0.200)	(0.213)	(0.162)
VTR	0.573*	0.321	0.410	0.473*	0.384	0.403
	(0.282)	(0.318)	(0.262)	(0.242)	(0.359)	(0.311)
VTR x COVID	-0.0772**	0.0596	0.0296	-0.151*	0.0447	-0.00320
	(0.0315)	(0.0338)	(0.0220)	(0.0747)	(0.0527)	(0.0440)
COVID	0.0207*	-0.0188	-0.0155	-0.0138	-0.0811***	-0.0676***
	(0.0103)	(0.0145)	(0.0108)	(0.0230)	(0.0184)	(0.0157)
Constant	4.486***	4.357***	4.380***	12.11***	11.72***	11.84***
	(0.205)	(0.175)	(0.136)	(0.179)	(0.229)	(0.194)
Industry FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	96,671	75,141	171,812	92,693	72,185	164,878
R-sq.	0.351	0.347	0.333	0.328	0.305	0.302

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Three-way standard errors clustered at the level of ISCO-1-digit occupations, nace 2 digits and years in parenthesis.

Table 8: COVID-related shadow cost of labor and market outcomes - alternative index

Dependent variable:	Employment (log)			Work volume (log)		
Sample:	Automatable occupations	Non automatable occupations	All occupations	Automatable occupations	Non automatable occupations	All occupations
	(1)	(2)	(3)	(4)	(5)	(6)
Female workers	0.0212	-0.0125	0.0004	-0.2104***	-0.2401***	-0.2377***
	(0.0397)	(0.0280)	(0.0307)	(0.0388)	(0.0272)	(0.0285)
Medium-skill	0.1603**	0.2103***	0.1634**	0.1636**	0.2506***	0.1741**
	(0.0560)	(0.0237)	(0.0442)	(0.0652)	(0.0378)	(0.0522)
High skill	0.0373	0.2024*	0.1008	0.0357	0.2771**	0.1247
	(0.0747)	(0.0884)	(0.0685)	(0.0892)	(0.1012)	(0.0840)
Age 25-49	0.1313***	0.1149**	0.1193***	0.1581**	0.2036***	0.1717***
	(0.0314)	(0.0359)	(0.0283)	(0.0523)	(0.0544)	(0.0433)
Age 50-64	-0.0362	-0.0388	-0.0398	-0.0506	0.0418	-0.0145
	(0.0427)	(0.0471)	(0.0364)	(0.0502)	(0.0687)	(0.0484)
Age 65 or more	-0.4824***	-0.4604***	-0.4534***	-1.4980***	-1.1997***	-1.3252***
	(0.0447)	(0.0683)	(0.0436)	(0.0631)	(0.1166)	(0.0921)
VTR*	0.5442**	0.3486***	0.3815**	0.4854**	0.3958**	0.3598*
	(0.1952)	(0.0872)	(0.1211)	(0.1590)	(0.1279)	(0.1653)
VTR x COVID	-0.0652**	0.0875	0.0544	-0.1109**	0.0674	0.0280
	(0.0196)	(0.0647)	(0.0332)	(0.0402)	(0.1001)	(0.0574)
RTI	-0.4895***	-0.1829	-0.2123*	-0.6769***	-0.1843	-0.2503*
	(0.0784)	(0.1121)	(0.0951)	(0.0466)	(0.1740)	(0.1233)
COVID	0.0183***	-0.0315	-0.0266	-0.0256	-0.0913**	-0.0806***
	(0.0024)	(0.0300)	(0.0157)	(0.0177)	(0.0356)	(0.0215)
Constant	4.5478***	4.3583***	4.4181***	12.1461***	11.7353***	11.8863***
	(0.1300)	(0.0934)	(0.0767)	(0.0839)	(0.1702)	(0.1271)
Industry FE	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	96,671	75,141	171,812	92,693	72,185	164,878
R-sq.	0.3517	0.3475	0.3325	0.3282	0.3050	0.3016

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. Two-way standard errors clustered at the level of ISCO-1-digit occupations and years in parenthesis.

References

Abeliansky, A. L., Algur, E., Bloom, D. E., and Prettner, K. (2020). The Future of Work: Meeting the Global Challenges of Demographic Change and Automation. *International Labour Review*, 159(3):285–306.

Abeliansky, A. L. and Prettner, K. (2023). Automation and Population Growth: Theory and Cross-Country Evidence. *Journal of Economic Behavior & Organization*, 208(April 2023):345–358.

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244.

Acemoglu, D. and Restrepo, P. (2022). Demographics and Automation. *The Review of Economic Studies*, 89(1):1–44.

Arntz, M., Gregory, T., and Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, Vol. 159:157–160.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, Vol. 118(No. 4):1279–1333.

Blanas, S. and Oikonomou, R. (2023). COVID-induced economic uncertainty, tasks and occupational demand. *Labour Economics*, 81:102335.

Bloom, D. E., Kuhn, M., and Prettner, K. (2022). Modern Infectious Diseases: Macroeconomic Impacts and Policy Responses. *Journal of Economic Literature*, 60(1):85–131.

Broady, K., Booth-Bell, D., Barr, A., and Perry, R. (2023). The Covid-19 Pandemic Spurred Growth in Automation: What Does this Mean for Minority Workers? *SSRN Electronic Journal*.

Chernoff, A. and Warman, C. (2023). COVID-19 and implications for automation. *Applied Economics*, 55(17):1939–1957.

De Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66:101885.

Di Porto, E. D., Naticchioni, P., and Scrutinio, V. (2022). Lockdown, essential sectors, and Covid-19: Lessons from Italy. *Journal of Health Economics*, 81:102572.

Ding, L. and Molina, J. S. (2020). "Forced Automation" by COVID-19? Early Trends from Current Population Survey Data. Community Affairs Discussion Paper 88713, Federal Reserve Bank of Philadelphia.

Eurofund (2022). Recovery from COVID-19: The changing structure of employment in the EU. Publications Office of the European Union, Luxembourg.

Fischer, K., Reade, J. J., and Schmal, W. B. (2022). What cannot be cured must be endured: The long-lasting effect of a COVID-19 infection on workplace productivity. *Labour Economics*, 79:102281.

Flisi, S. and Santangelo, G. (2022). Occupations in the European Labour Market During the COVID-19 Pandemic. *Intereconomics*, 57(2):120–126.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, Vol. 114(Issue C):254–280.

Hemous, D. and Olsen, M. (2022). The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality. *American Economic Journal: Macroeconomics*, 14(1):179–223.

Houstecka, A., Koh, D., and Santaeulalia-Llopis, R. (2021). Contagion at work: Occupations, industries and human contact. *Journal of Public Economics*, 200:104456.

Jones, C. I. (1995). R&D-Based Models of Economic Growth. *Journal of Political Economy*, 103(4):759–784.

Korinek, A. and Stiglitz, J. (2021). Artificial Intelligence, Globalization, and Strategies for Economic Development. Technical Report w28453, National Bureau of Economic Research, Cambridge, MA.

Krenz, A., Prettner, K., and Strulik, H. (2021). Robots, reshoring, and the lot of low-skilled workers. *European Economic Review*, 136:103744.

Marani, M., Katul, G. G., Pan, W. K., and Parolari, A. J. (2021). Intensity and frequency of extreme novel epidemics. *Proceedings of the National Academy of Sciences*, 118(35):e2105482118.

Pichler, S. and Ziebarth, N. R. (2017). The pros and cons of sick pay schemes: Testing for contagious presenteeism and noncontagious absenteeism behavior. *Journal of Public Economics*, 156:14–33.

Prettner, K. and Stoellinger, R. (2023). The viral transmission risk of occupations in austria and its implications for automatability. Mimeo.

Prettner, K. and Strulik, H. (2020). Innovation, Automation, and Inequality: Policy Challenges in the Race against the Machine. *Journal of Monetary Economics*, 116(December 2020):249–265.

Romer, P. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5):71–102.

Sostero, M., Milasi, S., Hurley, J., Fernandez Macias, E., and Bisello, M. (2020). Teleworkability and the COVID-19 crisis: a new digital divide? Technical Report 05, JRC Working Papers Series on Labour, Education and Technology.