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Pandemics and Automation: Will the Lost Jobs Come Back?

by Tahsin Saadi Sedik and Jiae Yoo

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Pandemics and Automation: Will the Lost Jobs Come Back?[1]

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Abstract

COVID-19 has exacerbated concerns about the rise of the robots and other automation technologies. This paper analyzes empirically the impact of past major pandemics on robot adoption and inequality. First, we find that pandemic events accelerate robot adoption, especially when the health impact is severe and is associated with a significant economic downturn. Second, while robots may raise productivity, they could also increase inequality by displacing low-skilled workers. We find that following a pandemic, the increase in inequality over the medium term is larger for economies with higher robot density and where new robot adoption has increased more. Our results suggest that the concerns about the rise of the robots amid the COVID-19 pandemic seem justified.

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I. Introduction and Related Literature

Long before COVID-19, the acceleration in automation was already causing unprecedented changes in work. One of the most notable and much discussed examples of automation technologies is the use of industrial robots. Robotics were undergoing a "Cambrian explosion," leading to a massive increase in the diversification and applicability of robots, supported by exponential growth in technology (Pratt, 2015; McAfee and Brynjolfsson, 2017). Like other technological changes, by reducing costs and improving productivity, robots may boost economic growth. But the fear is that they may also disrupt labor markets in transition, as they take over certain tasks and make traditional jobs obsolete. Moreover, robots do not affect all workers in the same way. Low-skilled workers are more at risk of displacement by robots than high-skilled workers, reinforcing inequality dynamics (Acemoglu and Restrepo, 2020).

COVID-19 has exacerbated concerns about the future of jobs. The pandemic is taking a heavy toll on labor markets, with record high unemployment rates. In tandem, the crisis is reshaping the nature of work, including by increasing telework and forcing automation, with significant negative consequences for low-wage workers and inequality (Autor and Reynolds, 2020). The fear is that the COVID-19 pandemic may accelerate the pace of automation, raising the possibility of a jobless recovery. A recent survey of business leaders and human resource strategists of large companies from around the world shows that over 80 percent are accelerating the digitalization of their work processes and expanding their use of remote work, and 50 percent indicate that they will accelerate the automation of jobs in their companies (World Economic Forum, 2020).

Against this background, this paper focuses on the following two questions. Will COVID-19 accelerate robotization? What will be the distributional impact of robotization following pandemics?

To answer these questions, we empirically analyze the impact of past major pandemics on robot adoption and how it affects inequality. We use local projection method (Jordà, 2005) and robot data at the sectoral levels from the International Federation of Robotics covering 18 industries in 40 countries, from Americas, Asia, and Europe, over 2000-2018. Our results suggest that that robot adoption (measured by new robot installations per 1000 employees) increases after pandemic events, especially when the health impact is severe and is associated with a significant economic downturn. While automation raises productivity (Brynjolfsson and McAfee, 2014; Acemoglu and Restrepo, 2018; Graetz and Michaels, 2018), it also increases inequality by displacing low-skilled workers (Acemoglu and Restrepo, 2020). Indeed, we find that following a pandemic, the increase in inequality, measured by net (post tax and transfer) Gini coefficient, over the medium term is larger for economies with higher robot density (the number of the existing stock of industrial robots per 1000 workers) and where new robot adoption (the cumulative sum of the new robot installations in the years following a pandemic) has increased more. These results suggest that the distributional effects of COVID-19 could be sizeable through an acceleration of robotization. Looking forward, a corollary of our results is that as automation and robotization are accelerating from still low levels, they are expected to become even more important drivers of inequality in the future.

Our paper is related to several strands of the literature. First, our work contributes to the burgeoning literature on the impact of pandemics on automation. Using a new Keynesian DSGE model, Leduc and Liu (2020) find that, while pandemics reduce aggregate demand and new investment, pandemic-induced uncertainty about worker productivity incentivizes firms to automate on net, as they try to anticipate future labor disruptions from pandemics. In the context of COVID-19, indeed, Caselli, Fracasso and Traverso (2020) find that industries that make greater use of robots face lower risk of contagion, and therefore less exposed to the risks related to lockdowns. In terms of job consequences of COVID-19 and automation, Chernoff and Warman (2020) find that women with mid to low levels of wages and education are at the highest risks, as their jobs have high automation potential and exhibit a high risk of infection.

Our work also broadly relates to the literature on jobless recoveries. Many have documented jobless recoveries where employment recovers very slowly for years after large negative shocks such as recessions (Groshen and Potter, 2003; Bernanke, 2003). Jaimovich and Siu (2020) find that jobless recoveries in recent decades are largely led by disappearing routine occupations, and essentially all of it occurs in economic downturns. During normal times, high opportunity costs of investing in production technologies and related adjustment costs may discourage firms from reallocating resources to technology adoption. Large shocks like recessions, or pandemics in the current context, can provide firms a catalyst to restructure production toward labor-saving technologies, as they lower the opportunity cost of adjustment (Hall, 2005) or change the costs and benefits of layoffs (Mortensen and Pissarides, 1994; Berger, 2012). Hershbein and Kahn (2018) find that the global financial crisis (GFC) accelerated the routine-biased technological change. Displaced workers are then forced into time-consuming transitions to different occupations and sectors, resulting in a slow job recovery. A major shock like COVID-19 that combines health and economic crises could lead to a jobless recovery, especially in the face of the accelerated robot adoption. Ding and Molina (2020) find that since COVID-19, layoffs have been higher in industries that can be automated, raising the risk of permanent losses of automatable jobs during the recovery.

Finally, our paper contributes to the literature on the distributional impact of pandemics, by linking the increase of inequality to automation. Furceri, Loungani, Ostry and Pizzuto (2020) provide evidence that major epidemics over the past two decades, even though much smaller in scale than COVID-19, have led to persistent increases in inequality. Saadi Sedik and Xu (2020) show that pandemics, by reducing growth and raising inequality, led to a significant increase in social unrest, which in turn is associated with lower growth and higher inequality, forming a vicious cycle. We contribute to this literature by establishing that pandemics lead to an increase in inequality through an acceleration in robotization. Indeed, robots tend to disproportionately displace jobs that involve routine and manual tasks which have traditionally been performed by low-skilled workers with lower earnings (Graetz and Michaels, 2018; Autor and Reynolds, 2020).[2] Furthermore, Acemoglu and Restrepo (2020) find that automation in recent decades significantly contributed to the growing skill premium, contributing to rising inequality.

The rest of the paper is organized as follows. Section II describes the key data used in the analysis. Section III details recent trends in robot adoption. Section IV assesses the impact of past pandemics on robot adoption. Section V analyzes the impact of pandemics on inequality through an increase in robotization. The last section concludes and discusses policy implications.

II. Data

The main source of data of robots is the International Federation of Robotics (2018a). The IFR compiles information on worldwide shipments and stocks of industrial robots from national federations of robot manufacturers. An industrial robot is “an automatically controlled, reprogrammable, multipurpose, manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications,” as defined by International Organization for Standardization (ISO). This excludes dedicated industrial robots that serve one purpose such as equipment dedicated for loading/unloading of machine tools and dedicated assembly equipment (IFR, 2018a). Consolidating data provided by nearly all industrial robot suppliers worldwide, the IFR provides robot shipment and stock data for 75 countries, with the industry breakdown according to the International Standard Industrial Classification (ISIC) of all economic activities revisions 4 from 2010 onward, and 2 or 3 in earlier years. The earliest data start in 1993, available at the country level with the industry breakdown available only for a few cases. However, the data coverage, especially the industry breakdown, improves over the years. We focus on industrial robots and do not

[2] Related to this is the literature on job polarization. This literature argues that the share of employment in middle-wage occupations has declined, mainly in advanced economies, while employment in both high- and low-wage jobs has increased (Acemoglu, 1999; Autor, Katz, and Kearney, 2006; Goos and Manning, 2007; Goos, Manning, and Salomons, 2009; Acemoglu and Autor, 2011; Goos, Manning, and Salomons, 2014; Michaels, Natraj, and Van Reenen, 2014). This hollowing out of the middle is linked to the disappearance of occupations focused on routine tasks (Jaimovich and Siu, 2020). The polarization process was accelerated by the Global Financial Crisis (Autor, 2010; Brynjolfsson and McAfee, 2011). Job polarization is primarily due to progress in technologies that substitute for labor in performing routine tasks (Autor, Levy, and Murnane, 2003). However, the COVID-19 pandemic is reshaping the nature of work, with negative consequences for both low-wage jobs and middle-paid jobs (Autor and Reynolds, 2020).

consider service robots, because the coverage of service robot data is sparse and likely underestimates the usage.[3]

We use the data from the World Input-Output Database (WIOD), Socio-Economic Accounts, for the industry-level employment data. The 2016 WIOD (Timmer and others, 2015) provides information on labor between 2000 and 2014 for 43 countries and 56 industries at 2-digit ISIC revision 4 level. We merge these data with the robotics data to measure the robot usage relative to the size of employment for each industry and country. The WIOD also provides the industry-level data on the wage and capital, which we later use as control variables in regression analyses. The combined IFR and WIOD data cover 18 industries in 40 countries for the period 2000-2014 (Table A.1).[4]

We measure income inequality by Gini coefficient estimates from the Standardized World Income Inequality Database (SWIID 8.2). This data combines information from Luxembourg Income Study and various sources and provides comparable Gini indices of disposable and market income inequality for a large number of countries starting from 1961 onward. Solt (2020) provides details on the construction of this dataset.

We identify pandemic events, following Ma, Roger and Zhou (2020) and Furceri, Loungani, Ostry and Pizzuto (2020). We focus on four major past pandemics within our data coverage: SARS in 2003, H1N1 in 2009, MERS in 2012, and Ebola in 2014.[5] The most widespread one was H1N1 (Swine Flu Influenza), with more than 6,000,000 confirmed cases across 148 countries and about 19,000 fatalities. Excluding H1N1—which spread across all regions—the other three events were mostly confined to specific regions: SARS and MERS in Asia, and Ebola in Africa. In terms of average mortality rates (deaths/confirmed cases), Ebola and MERS were the most fatal, followed by SARS and H1N1. The list of countries in our sample that are affected by each event is given in Table A.2. We construct a dummy variable to capture pandemic events, which takes the value of 1 when WHO declares a pandemic for the country and 0 otherwise. Alternatively, we also use other measures of pandemics such as the number of confirmed cases and deaths related to pandemics to take into account the heterogeneity of the intensity of pandemic events across economies.

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[3] The IFR underscores that the data reported "underestimate the true sales figures and installed base of robots. They should therefore be seen as a minimum level of the installed base of service robots," (IFR, 2018b). This is in part because the service robot industry is more diverse and less tangible than the industrial robot industry.

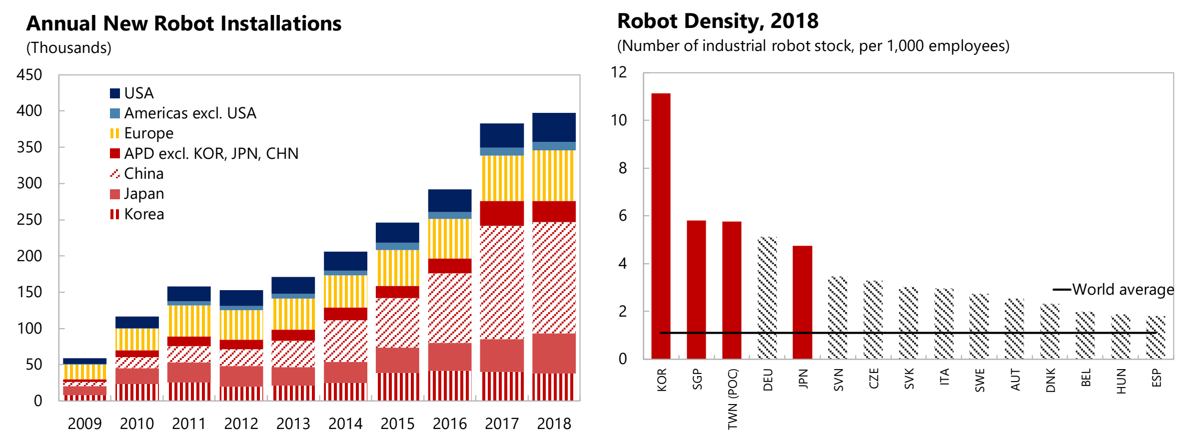
[4] However, the robot data are available until 2018, allowing us to estimate the impact of pandemics on robot adoption up to four years after 2014.

[5] Zika in 2016 is not considered in this analysis because other important variables for the analysis (i.e., the industry-level labor and capital-related data from the WIOD) are available only until 2014. Also, to capture the full impact of Zika over the medium term (four years after the shock), we would need robot data until 2020.

III. Recent Trends in Robot Usage

The use of industrial robots has increased dramatically since the GFC. After a brief interruption during the peak of the GFC, the increase in robot usage picked up its pace over the last decade. The acceleration has been mostly driven by countries in Asia, especially China (Figure 1, left chart). In recent years, about two-thirds of new robots in the world were installed in Asia, including about a half in China. In terms of the robot density (the number of the existing stock of industrial robots per 1000 workers), Korea, Singapore and Taiwan POC are the global leaders, followed by Germany and Japan (Figure 1, right chart; and IMF, 2018).

Figure 1. Use of Industrial Robots



Source: International Federation of Robotics, International Labor Organization

Despite the sharp overall increase, the use of industrial robots is still concentrated in certain manufacturing industries. In addition to the cross-country differences in the intensity of robot usage, the density varies widely across different industries. In any given economy, most industrial robots are used in the manufacturing industry, even though some robots are being reported in other sectors. Furthermore, within the manufacturing industry, automotive manufacturing in particular is the most automated sub-industry by far. In some Asian economies, robot density is also high in electronics manufacturing sector (Figure 2).

Figure 2. Robot Density by Industry, Selected Economies, 2014

(Number of industrial robot stock, per 1000 employees, within each industry category)

		Breakdown by industry						Breakdown within the manufcaturing industry							
	All industries	Agriculture	Construction	Education	Energy	Mining	Manufacturing	Auto	Electrical	Plastic	Metal	Food	Glass	Paper	Textile
KOR	10.1	0.2	0.0	0.2	0.1	1.6	46.5	192.6	112.8	21.1	6.3	3.0	2.6	0.3	0.1
JPN	5.5	0.4	0.2	0.2	0.2	0.1	32.7	140.0	52.8	29.4	11.9	3.8	3.9	1.9	0.1
TWN (POC)	5.2			0.1	0.5	0.3	9.4	25.6	23.3	6.3	2.3	0.9	0.2	0.1	1.1
DEU	4.6	0.2	0.1	0.8	0.1	0.1	21.1	108.7	9.5	20.2	9.6	7.5	10.2	1.7	1.6
ITA	3.3	0.1	0.2	0.1	0.1	0.0	14.5	106.3	5.8	25.0	13.5	13.1	7.3	1.8	0.6
SVN	2.4	1.6	0.5	0.4			8.9	58.2	4.5	10.2	4.9	4.8	1.5	0.1	0.1
USA	1.5	0.1	0.0	0.1	0.0	0.0	14.3	116.3	21.7	10.2	6.0	5.2	0.7	0.3	0.2
CAN	0.5	0.0	0.0	0.1	0.0	0.0	4.0	38.5	2.0	2.3	1.3	2.8	0.2	0.1	
MEX	0.4		0.0	0.0		0.0	2.2	14.9	0.8	2.6	1.2	0.1	0.1	0.0	

Source: International Federation of Robotics, the World Input-Output Database (WIOD), Socio-Economic Accounts.
Note: The table shows the robot density as of 2014 for three economies that had the highest robot density in each region.

IV. Do Pandemics Accelerate Robotization?

We examine empirically whether pandemic events contribute to the increase in robot usage, using the local projection method proposed by Jordà (2005). This method does not impose dynamic restrictions and is flexible to accommodate nonlinearities in the dynamic responses. We estimate impulse response functions directly from local projections:

$$R_{i,c,t+k} = \beta^k D_{c,t} + \theta^k X_{i,c,t} + Controls + \varepsilon_{i,c,t+k} \qquad (1)$$

where $R_{i,c,t+k}$ represents robot adoption between t and $t+k$ (measured by the cumulative sum of the new robot installations in years between t and $t+k$, normalized by employment size at time t) in industry i in country c; $D_{c,t}$ is a dummy variable indicating a pandemic event that affects all industries in country c in year t; $X_{i,c,t}$ is a vector that includes three lags of the dependent variable and the pandemic dummy. We include industry and country fixed effects and time fixed effects (five-year dummies) to control for unobserved cross country, industry and time heterogeneity.[6] Country fixed effects control for country characteristics that do not vary over the period of the study and that may affect robot adoption. For example,

[6] Given that the pandemic variable is a dummy, we consider 5-year dummies rather than year dummies. Year dummies would absorb the effect of pandemic events that are widely spread. For instance, if we had COVID-19 data, a year dummy for 2020 would be perfectly correlated with the COVID pandemic event. This is the case for H1N1 pandemic where almost all countries in our sample were impacted (see Table A.2). The 5-year dummies approach is similar to the approach used by Ma, Rogers and Zhou (2020), where the use decade dummies.

they control for unchanged country specific employment protection legislation and tax regimes. Industry fixed effects control for unobserved industry-level technology and demand shocks and industry-specific susceptibility to robot adoption. Time fixed effect control for aggregate shocks and trends. These reduce the possibility of omitted variable bias. We also control for the world real GDP growth, as a proxy for global business cycle.

Furthermore, for robustness checks, we consider additional control variables such as log of wages and the ratio of capital to wages at the industry level (to capture the relative cost of human compared to robots, following Graetz and Michaels, 2018). We also include country-level controls, such as the level of economic development measured by GDP per capita (as advanced economies use more robots), population aging (as it can accelerate automation) and measures of trade and financial globalization (trade and offshoring of the production process can be an alternative to robotization, Fernández-Macías et al., 2020[7]—these global value chains depend heavily on cross-border capital flows, Bruno and Shin, 2019). These variables may also affect the probability of pandemic events.[8] Standard errors are clustered at the level of country and industry pair.

We estimate equation (1) for an unbalanced panel of 18 industries in 40 countries over the period 2000-2014, for each horizon (year) $k = 0, \dots, 4$.[9] That is, we estimate the impulse response functions, $\{\beta^k\}_{k=0}^{4}$, up to four years after the shock. Figure 3 shows the estimated dynamic response of robot adoption up to four years after a pandemic event. It shows the 90 percent confidence interval and one standard deviation band around the point estimates, using standard errors clustered at the level of country and industry pair. The vertical axis shows the estimated number of new robots installed in cumulative terms over the years, normalized by 1000 employees.

The results show that pandemics lead to an increase in robot adoption over time, with some lag. In the second year, we estimate that about 0.35 more new robots are installed per 1000 employees and 0.7 more new robots in four years after a pandemic event.

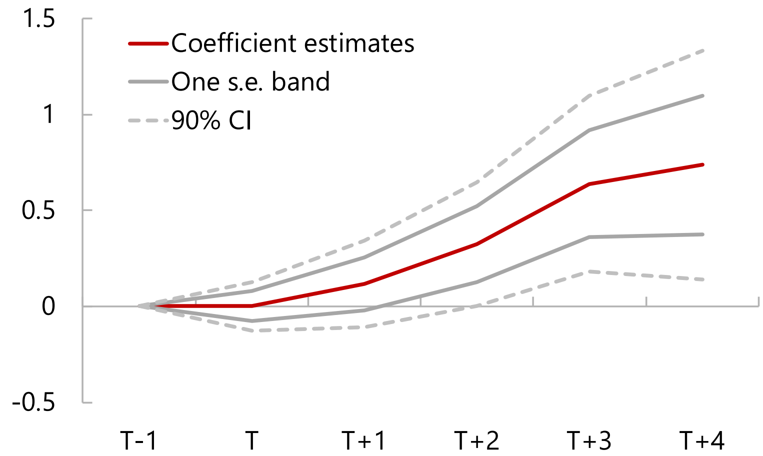
[7] Production is offshored to economies with cheap labor, but it could also be offshored to third countries with even more automated productive technologies.

[8] The occurrence of the pandemic events is, however, largely unpredictable and exogenous to the economy (Jordà et al., 2020). In other words, even without the controls, the coefficient β^k would still be unbiased. We also run a Granger causality test and found that the null hypothesis that pandemic dummy does not Granger-cause robot adoption is rejected at the 90 percent confidence level (p-value=0.07); however, the hypothesis that robot adoption does not Granger-cause pandemic dummy is not rejected (p-value=0.53).

[9] The robot variable is available until 2018, allowing us to estimate the robot adoption up to 4 years ($k = 0, \dots, 4$). That is, we capture the impact of shocks until 2018.

Figure 3. Robot Adoption and Pandemics

(Robot installation per 1000 employees in cumulative terms; T = pandemic year)



Source: Authors.
Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). The estimates are based on: $R_{i,c,t+k} = \beta^k D_{c,t} + \theta^k X_{i,c,t} + Controls + \varepsilon_{i,c,t+k}$. The dependent variable R is new robot installation per 1000 employees in cumulative term between t and $t + k$; D is a dummy indicating pandemic years; X denotes three lags of the dependent variable and the pandemic dummy. We control for industry and country fixed effects, and five-year dummies, as well as global business cycle (world real GDP growth). Standard errors are clustered at the country-industry pair level.

Our results are in line with the literature showing that firms undertake restructuring after large shocks like recessions and adjust production toward labor-saving technologies (Hershbein and Kahn, 2018).[10] They are also consistent with recent studies showing that pandemic-induced uncertainty could add to the incentives for automation on net, despite its negative effects on aggregate demand, as firms try to anticipate future labor disruptions from pandemics (Leduc and Liu, 2020).[11]

The results are robust to a battery of robustness checks:

- First, we include several additional controls in the regression: industry-level controls such as the log of wage and the capital-to-wage ratio, and the economy-level macroeconomic variables such as income, and measures of trade and financial globalization, as well as an

[10] As highlighted by Hershbein and Kahn (2018), in boom times, high opportunity costs, or frictions such as adjustment costs, may inhibit resources from being reallocated optimally in the face of technological change. Recessions lower the opportunity cost and can produce large enough shocks to overcome these frictions.

[11] The rationale is that workers can be exposed to health risks, and social distancing measures can reduce labor productivity. But robots do not get sick. Automation provides a hedge against job uncertainty stemming from the pandemic. Note that robots may be infected with cyber viruses.

indicator of population aging (share of population age 65 and over). The results are reported in Table A.3 and Figure A.1, and they remain very similar to the baseline results.

- Second, we conduct the same analysis, excluding the episode of H1N1. The H1N1 pandemic was the most widespread across regions and coincided with the GFC in 2009, which also affected many economies globally. The size of the coefficient estimates excluding the H1N1 pandemic is similar to the ones including all pandemics (Figure A.1). However, when excluding H1N1, the number of pandemic episodes within the sample period and economies drops by more than half, and estimates become less precise.

- Third, we use measures that capture the intensity of pandemic events (i.e., the number of infection cases and deaths related to pandemics), instead of using a binary variable for pandemic events. This also alleviates the issues related to the fact that H1N1 coincided with the GFC in 2019. The cross-country heterogeneity in the H1N1 exposures, which is exogenous to the GFC, would help reaffirm that the results are not driven by the GFC (Ma, Rogers and Zhou, 2020). The results in Figure A.2 show that more intense pandemics tend to have greater impact on robot adoption.

- Fourth, to further control for business cycles, we also include a recession dummy (measured as a negative growth or 20 percentile lower growth at country level). This also addresses the concern that some pandemic events during the sample period may have occurred during a period of recession (e.g., H1N1 in 2009). Figure A.3 shows that the results are broadly similar to the baseline.

- Fifth, we use log of the robot adoption variable to mitigate the issues related the long tail in the distribution of the robotics data (Graetz and Michaels, 2018), while allowing a direct interpretation of the results in a relative term (percent increase in new robot installation). The results confirm that pandemics accelerate robot adoption over the medium term, as shown in the Figure A.4. Four years after a pandemic event, robot adoption is about 20 percent higher compared to a no pandemic event.

Furthermore, we assess the impact of pandemics on robotization conditional on the severity of pandemic events. Specifically, we augment the baseline specification to allow for the impact of pandemics to vary with the severity of pandemics in terms of health risks and growth, based on the smooth transition autoregressive model (Granger and Teräsvirta, 1993; Teräsvirta, 1998):

$$R_{i,c,t+k} = F(z_{ct})\left[\beta_L^k D_{c,t} + \theta_L^k X_{i,c,t}\right] + \left[1 - F(z_{it})\right]\left[\beta_H^k D_{c,t} + \theta_H^k X_{i,c,t}\right] + Controls + \varepsilon_{i,c,t+k},$$

$$\text{with } F(z_{ct}) = \frac{exp^{-\gamma z_{ct}}}{(1 - exp^{-\gamma z_{ct}})}, \quad \gamma = 3.5\ , \tag{2}$$

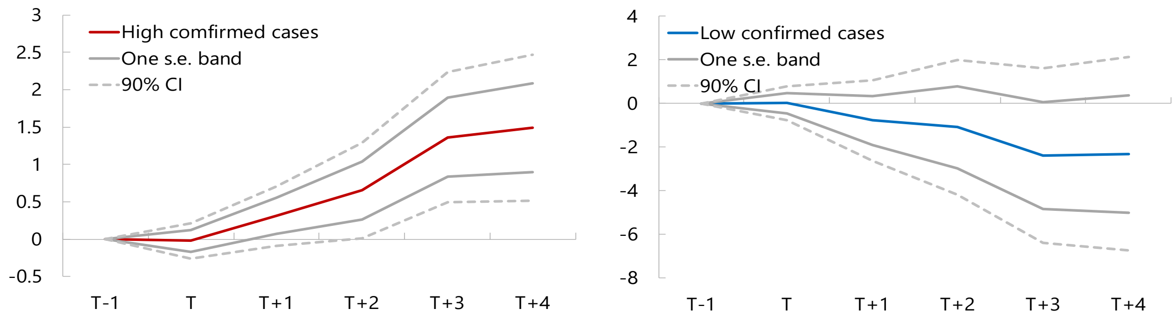
where z is an indicator of the severity of the pandemic—the number confirmed cases or deaths in log as a proxy for health impact, or real GDP growth in terms of economic impact—normalized to have zero mean and a unit variance. The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that $F(z)$ can be interpreted as the probability of being in a given state. The coefficients β_L^k and β_H^k capture the impact of pandemic on robotization at each horizon k in case of very low levels of z ($F(z_{ct})$ approaches one when z goes to minus infinity) and high levels of z ($1 - F(z_{ct})$ approaches one when z goes to plus infinity), respectively. We choose γ=3.5, following Tenreyro and Thwaites (2016), and Furceri, Loungani, Ostry and Pizzuto (2020). This approach can directly test whether the effect of pandemics varies depending on its severity in terms of health and growth impact, while allowing the effect to vary smoothly across states thus making the impulse response function more stable and precise.

The results in Figure 4 (and Table A.3) show that the impact of pandemics on robot usage varies with their severity. For those pandemics associated with severe health consequences (i.e., a larger number of cases or deaths) and those with a significant economic downturn, the effect is statistically significant. The impact is not significant for events associated with lower case number, lower death mortality, and milder growth impact.

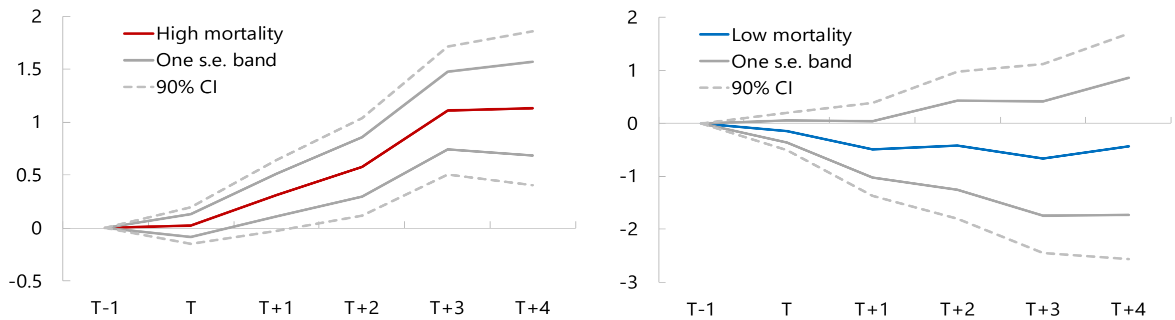
Figure 4. Robot Adoption: Impact by the Severity of the Pandemic

(Robot installation per 1000 employees in cumulative terms; T = pandemic year)

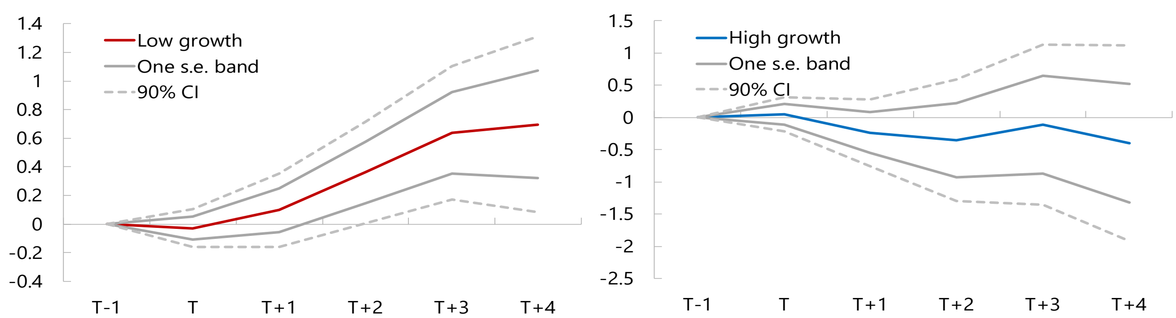
Health impact (case numbers in log)



Health impact (number of deaths in log)



Economic impact (real GDP growth)



Source: Authors.

Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). The estimates are based on: $R_{i,c,t+k} = F(z_{it})[\beta_L^k D_{c,t} + \theta_L^k X_{i,c,t}] + [1 - F(z_{it})][\beta_H^k D_{c,t} + \theta_H^k X_{i,c,t}] + Controls + \varepsilon_{i,c,t+k}$. The dependent variable R is new robot installations per 1000 employees in cumulative terms between t and $t+k$; D is a dummy indicating pandemic years; X denotes three lags of the dependent variable and the pandemic dummy; $F(z_{ct})$ is an indicator function of the severity of pandemic, and the coefficient β_H^k captures the impact of a pandemic with severe health (two upper panels) and economic impact (lower panel) and β_L^k captures the impact of mild pandemics. The estimation controls for industry and country fixed effects, five-year dummies, and global business cycle. Standard errors are clustered at the country-industry pair level.

V. Pandemics, Robotization, and Inequality

To examine the role of robot adoption in the distributional impact of pandemics, we estimate the impact of pandemics on changes in Gini coefficients while allowing the coefficients on the pandemic variable to vary depending on the level of robot density and adoption:

$$G_{c,t+k} - G_{c,t-1} = \sum_{q \in \{H,M,L\}} \beta^{k,q} R^{q}_{c,t} D_{c,t} + \sum_{q \in \{H,M,L\}} \theta^{k,q} R^{q}_{c,t} X_{c,t} + Controls + \varepsilon_{i,c,t} \quad (3)$$

where $G_{c,t+k} - G_{c,t-1}$ denotes the changes in the log of net Gini coefficients in country c between the year $t-1$ and $t+k$;[12] $R^{q}_{c,t}$ is a set of dummy variables indicating the level of robot adoption (i.e., the stock of robot per 1000 employees): high (top 1/3, H, i.e., more than 2.3 robots per 1000 employees in the sample), intermediate (middle 1/3, M), and low (bottom 1/3, L). As an alternative, we also divide the sample by the pace of robot adoption measured by the cumulative sum of new robot installations over the next 5 years, rather than the stock, normalized by the size of employment at time t. $D_{c,t}$ is a dummy indicating pandemic years. $X_{c,t}$ denotes three lags of the dependent variable and the pandemic dummy. The estimation controls for country fixed effects, time dummies, and global business cycle.

The results show that the increase in inequality tends to be higher, and statistically significant, for cases with high robot density than with low density (Figure 5, left). We obtain similar results when we use the pace of robot adoption. Inequality rise faster following pandemics where robot adoption is at a faster pace (Figure 5, right).[13] These results suggest that the robot adoption following pandemics could have a sizable impact on inequality.[14]

We obtain similar results when we allow smooth transitions, similar to the specification in equation (2), except that transition is a function of robot density or the pace of robot adoption (Figure A.5).

Our results are consistent with the literature on pandemics and inequality and the literature on skill-biased technological changes. Furceri, Loungani, Ostry and Pizzuto (2020) find that past pandemics have raised inequality and led to increases in the Gini coefficient. We show that one channel through which pandemics lead to an increase in inequality is the rise of

[12] Since the Gini coefficients are available only at the country level, not at the industry level, we run regressions in this section using country-level panel data. While losing the industry-level details, this expands the sample to 66 countries over 1993-2014.

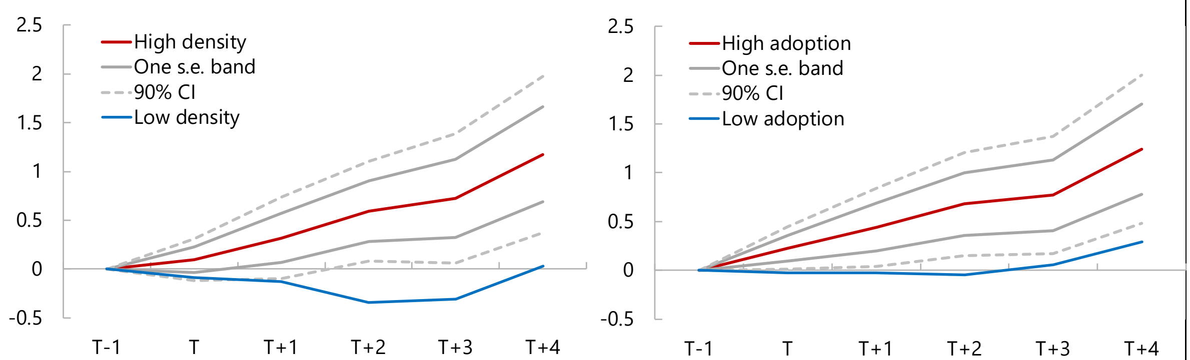
[13] We obtain similar results if we use the cumulative sum of new robot installation over the next 4 years, instead of 5 years.

[14] We run a Granger causality test and found that the null hypothesis that pandemic dummy does not Granger-cause Gini is rejected at the 90 percent confidence level (p-value=0.03); however, the hypothesis that Gini does not Granger-cause pandemic dummy is not rejected (p-value=0.22).

robots following pandemics. The acceleration in automation can worsen inequality dynamics because robots do not affect all workers in the same way. Jobs that are most susceptible to automation tend to involve routine and manual tasks, and those jobs have traditionally been performed by workers with mid-level skills or low-skilled workers (Graetz and Michaels, 2018; Autor and Reynolds, 2020). Therefore, low-skilled workers, who also tend to have lower earnings, are more at risk from displacement by robots than high-skilled workers. Moreover, robots create new tasks, but they benefit mainly high-skilled workers, reinforcing inequality dynamics (Acemoglu and Restrepo, 2020). Through the uneven impact on workers with different skill levels, robots can contribute to the rise in inequality.

Figure 5. Changes in Net Gini Following Pandemics by Robotization Levels
(Percentage points; T = pandemic year)

By robot density (existing stock of robots) | **By robot adoption** (pace of the increase in robots)



Source: Authors.
Note: Impulse responses are estimated using a sample of 66 economies over the period 1993-2014, using local projection method (Jorda, 2005), allowing the coefficients on pandemic variables to vary depending on robot density and the pace of robot adoption (top, medium, and bottom 1/3), where the adoption pace is proxied by the cumulative sum of new robot installation over the next 5 years. The estimates are based on: $\Delta G_{c,t+k} = \sum_{q\in\{H,M,L\}} \beta^{k,q} R^{q}_{c,t} D_{c,t} + \sum_{q\in\{H,M,L\}} \theta^{k,q} R^{q}_{c,t} X_{c,t} + Controls + \varepsilon_{i,c,t}$. The dependent variable is the changes in net Gini in logs; D is a dummy indicating pandemic years; R^q denotes a dummy indicating high/medium/low robot density or adoption; X denotes three lags of the dependent variable and the pandemic dummy. The estimation controls for country fixed effects, time dummies, and global business cycle. Standard errors are clustered at the country level.

VI. Conclusion and Policy Discussions

The COVID-19 pandemic has exacerbated inequality of income and opportunity by its disproportionate impact on low-skilled workers, women, youths, and those who may be already on the margins of the labor market. Moreover, we show, based on the experience from past major pandemics, that the adverse distributional effects could be even larger in the medium term through an acceleration of robot adoption, which mainly displace low-skilled workers. Left unchecked, growing disparities will lead to long-lasting grievances and ultimately to social unrest, forming a vicious cycle (Saadi Sedik and Xu, 2020).

Policymakers need to pay special attention to preventing scarring effects on the livelihoods of the most vulnerable in their societies. In the short term, policymakers need to prevent scarring in the labor market. Better and smarter targeting of limited fiscal support is essential, both for people and for firms. Targeted support provides greater bang for the buck, both in protecting lives and livelihoods (Jurzyk et al., 2020).

As automation intensifies following the COVID-19 crisis, more workers will need to find new jobs, especially those who are less skilled. Policies to mitigate the sizable adverse impacts on inequality also include revamping education to meet the demand for more flexible skill sets and lifelong learning, as well as new training, especially for the most adversely affected workers, and reducing skill mismatches between workers and jobs.

These measures may still fall short if the training involves acquiring a substantively different and challenging set of skills, raising the possibility of a persistent increase in dropouts. It is therefore important to address medium-term social challenges, including through income redistribution and safety nets.

The recent literature has considered wide-range policies to address automation and inequality. These include raising unemployment insurance benefits, introducing a universal basic income, increasing transfers to labor force non-participants, making the tax system more progressive, and taxing robots. Policymakers will face tradeoffs in implementing these policies.[15] For example, Guerreiro, Rebelo and Teles (2020) show that it may be optimal to tax robots in the short run in order to protect current routine workers who cannot acquire non-routine skills. However, it is not optimal in the long run as it disincentivizes those in the future to obtain non-routine skills.

As Korinek and Stiglitz (2018) show, policies to soften the labor market impact of new technologies can make a difference to improve welfare. The more willing society is to support the necessary transition and provide support to those who are left behind, the faster the pace of innovation that society can accommodate while still ensuring that the outcomes are welfare improvements, with all members of the society better off.

[15] For example, Jaimovich, Saporta-Eksten, Siu and Yedid-Levi (2020) show that while raising unemployment insurance benefits modestly succeeds at improving the average welfare, introducing a universal basic income and increasing transfers to labor force non-participants impose large welfare losses on high-wage workers and are very costly in terms of aggregate income. In contrast, they find that making the tax system more progressive, with a reduction in the taxes levied on low-earners and balancing the budget by increasing the taxes on high-earners, can achieve much of the redistribution gains and much smaller welfare losses for high-income earners without lowering aggregate output.

APPENDICES

Table A.1. Data Sources and Descriptive Statistics

Variable	Source	Obs.	Med.	Mean	Std. dev.
Sample = 18 industries in 40 economies, during the period 2000-2014					
Annual robot installation	IFR	4320	9.0	226.6	1172.2
Annual robot installation, per 1000 workers	IFR, WIOD	4320	0.1	0.8	2.3
Robot operating stock	IFR	4320	74.5	1994.3	10431.4
Robot operating stock, per 1000 workers	IFR, WIOD	4320	8.1	70.1	226.5
Number of confirmed cases	Furceri et al. (2020)	4320	0.0	22909.1	228611.2
Number of deaths related to pandemics	Furceri et al. (2020)	4320	0.0	35.9	255.3
Real GDP growth	WEO (2020)	4320	1.8	1.5	3.0
Net Gini	SIID 8.2	2119	29.4	29.4	4.9
Pandemic events	Furceri et al. (2020)	4320	0.0	0.2	0.4
					N.Obs with Pand. Dumm. = 1
SARS (2003)					78
H1N1 (2009)					392
MERS (2012)					164
Ebola (2014)					72

IFR = International Federation of Robotics

WIOD = World Input-Output Data, Socio Economic Accounts

Table A.2. List of Pandemics and Epidemic Episodes

Starting year	Event	Affected countries	N. countries
2003	SARS	DEU, ESP, FRA, GBR, ITA, SWE	6
2009	H1N1	AUS, AUT, BEL, BGR, BRA, CHE, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IDN, IND, IRL, ITA, JPN, KOR, LTU, LVA, MLT, NLD, NOR, POL, PRT, ROU, RUS, SVK, SVN, SWE, TUR, USA	37
2012	MERS	AUT, DEU, FRA, GBR, GRC, ITA, KOR, NLD, TUR, USA,	10
2014	Ebola	ESP, GBR, ITA, USA	4

Source: Ma, Rogers and Zhou (2020)

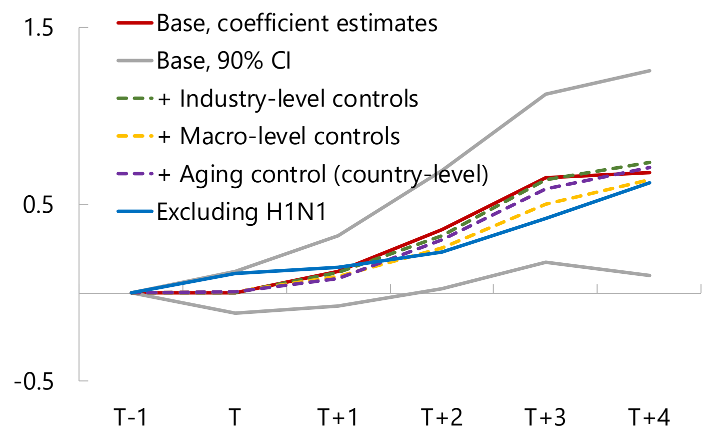
Table A.3. Impact of Pandemics on Robot Adoption

Dep. Var. = Robot adoption													
	Panel A. Robot adoption and pandemics				Panel B. Robot adoption and pandemic: impact by the severity of the pandemic								
					By health impact (case)			By health impact (mortality)			By economic impact		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Overall				**High confirmed cases**			**High mortality**			**Low growth**		
T	0.002	-0.000	0.009	0.004	-0.022	0.048	0.072	0.011	0.024	0.018	-0.009	-0.029	0.007
	(0.072)	(0.078)	(0.085)	(0.081)	(0.143)	(0.137)	(0.169)	(0.113)	(0.107)	(0.120)	(0.074)	(0.080)	(0.075)
T+1	0.122	0.116	0.094	0.083	0.312	0.439	0.449	0.324	0.311	0.330	0.116	0.097	0.129
	(0.121)	(0.137)	(0.143)	(0.131)	(0.243)	(0.272)	(0.342)	(0.199)	(0.203)	(0.214)	(0.140)	(0.155)	(0.144)
T+2	0.357*	0.324*	0.255	0.298	0.652*	0.783**	0.745*	0.627**	0.576**	0.590*	0.398*	0.362*	0.369*
	(0.204)	(0.196)	(0.194)	(0.189)	(0.387)	(0.365)	(0.441)	(0.306)	(0.280)	(0.320)	(0.214)	(0.216)	(0.209)
T+3	0.649**	0.638**	0.499*	0.587**	1.364**	1.494***	1.390**	1.180***	1.109***	1.077**	0.618**	0.637**	0.509*
	(0.288)	(0.279)	(0.289)	(0.290)	(0.531)	(0.505)	(0.595)	(0.414)	(0.366)	(0.424)	(0.285)	(0.284)	(0.279)
T+4	0.677*	0.736**	0.638*	0.709**	1.491**	1.564**	1.510**	1.074**	1.129**	0.935**	0.672*	0.697*	0.459
	(0.351)	(0.362)	(0.369)	(0.355)	(0.596)	(0.608)	(0.712)	(0.433)	(0.442)	(0.434)	(0.371)	(0.374)	(0.367)
					Low confirmed cases			**Low mortality**			**High growth**		
T					0.009	-0.111	-0.205	-0.136	-0.151	-0.138	-0.104	0.047	-0.124
					(0.470)	(0.450)	(0.524)	(0.189)	(0.211)	(0.193)	(0.174)	(0.160)	(0.187)
T+1					-0.782	-1.030	-1.126	-0.419	-0.488	-0.461	-0.404	-0.234	-0.385
					(1.122)	(1.078)	(1.264)	(0.498)	(0.532)	(0.507)	(0.347)	(0.314)	(0.346)
T+2					-1.093	-1.420	-1.515	-0.315	-0.414	-0.382	-0.539	-0.357	-0.444
					(1.879)	(1.781)	(2.007)	(0.803)	(0.846)	(0.808)	(0.622)	(0.574)	(0.599)
T+3					-2.387	-2.737	-2.818	-0.537	-0.664	-0.605	-0.275	-0.111	-0.088
					(2.439)	(2.327)	(2.573)	(1.016)	(1.081)	(1.018)	(0.798)	(0.756)	(0.756)
T+4					-2.317	-2.356	-2.486	-0.472	-0.428	-0.601	-0.456	-0.399	-0.095
					(2.694)	(2.689)	(2.983)	(1.296)	(1.293)	(1.310)	(0.912)	(0.923)	(0.855)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5-Year dumm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Global biz.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry ctrl.		Yes	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Country ctrl.			Yes	Yes			Yes			Yes			Yes
Aging ctrl.				Yes									
Obs (T)	4,188	3,621	3,476	3,476	4,188	3,621	3,476	4,188	3,621	4,084	4,188	3,621	4,084
F-stat.	152.31	101.99	121.29	e(F)	191.06	135.12	134.32	166.17	128.86	165.13	309.06	210.83	350.27
Obs (T+1)	4,183	3,616	3,473	3,473	4,183	3,616	3,473	4,183	3,616	4,081	4,183	3,616	4,081
F-stat.	95.11	75.37	81.93	e(F)	105.33	86.20	93.02	82.24	84.07	87.17	216.48	114.08	250.74
Obs (T+2)	4,178	3,611	3,470	3,470	4,178	3,611	3,470	4,178	3,611	4,078	4,178	3,611	4,078
F-stat.	71.50	65.20	70.90	e(F)	71.45	84.43	106.26	67.86	72.49	70.98	214.90	133.54	270.05
Obs (T+3)	4,173	3,608	3,468	3,468	4,173	3,608	3,468	4,173	3,608	4,074	4,173	3,608	4,074
F-stat.	62.35	51.71	61.95	e(F)	71.79	56.96	78.64	61.48	61.73	66.08	219.93	125.94	271.70
Obs (T+4)	3,603	3,603	3,464	3,464	3,603	3,603	3,464	3,603	3,603	3,520	3,603	3,603	3,520
F-stat.	47.25	43.43	52.21	e(F)	41.36	42.32	55.53	41.23	46.93	45.80	85.85	87.02	93.96

Source: Authors.

Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). Panel A presents the estimates on the impact of pandemics, based on $\boldsymbol{R_{i,c,t+k} = \beta^k D_{c,t} + \theta^k X_{i,c,t} + Controls + \varepsilon_{i,c,t+k}}$, considering different sets of control variables. The dependent variable $\boldsymbol{R}$ is new robot installations per 1000 employees in cumulative terms between $\boldsymbol{t}$ and $\boldsymbol{t+k}$; $\boldsymbol{D}$ is a dummy indicating pandemic years; $\boldsymbol{X}$ denotes three lags of the dependent variable and the pandemic dummy. It also controls for industry and country fixed effects, five-year dummies, and global business cycle. Panel B presents the estimates by allowing the impact of pandemics to vary by their severity: $\boldsymbol{R_{i,c,t+k} = F(z_{it})\left[\beta_L^k D_{c,t} + \theta_L^k X_{i,c,t}\right] + [1 - F(z_{it})]\left[\beta_H^k D_{c,t} + \theta_H^k X_{i,c,t}\right] + Controls + \varepsilon_{i,c,t+k}}$. $\boldsymbol{F(z_{ct})}$ is an indicator function of the severity of pandemics, i.e., the probability of being in a severe pandemic, and the coefficient $\boldsymbol{\beta_H^k}$ captures the impact of a pandemic with severe health and economic impact (upper panel) and $\boldsymbol{\beta_L^k}$ captures the impact of mild pandemics (lower panel). Standard errors are clustered at the country-industry pair level.

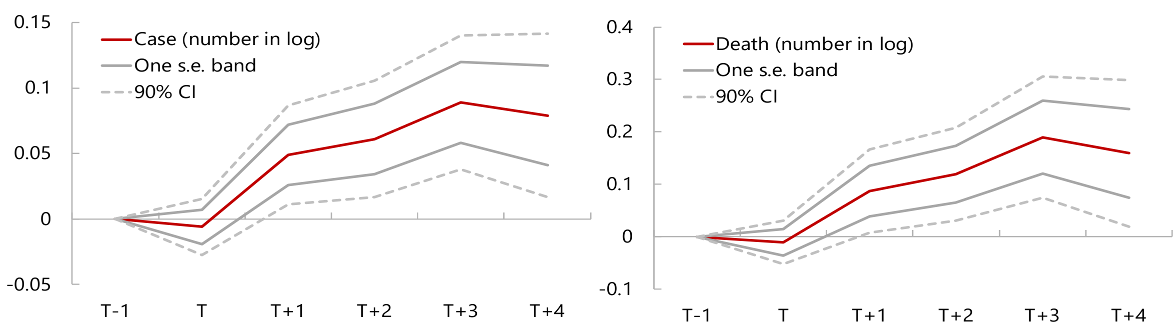
Figure A.1. Robot Adoption and Pandemics, with Additional Control Variables
(Robot installation per 1000 employees in cumulative terms; T = pandemic year)



Source: Authors.
Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). The estimates are based on: $R_{i,c,t+k} = \beta^k D_{c,t} + \theta^k X_{i,c,t} + Controls + \varepsilon_{i,c,t+k}$. The dependent variable R is new robot installations per 1000 employees in cumulative terms between t and $t+k$; D is a dummy indicating pandemic years; X denotes three lags of the dependent variable and the pandemic dummy. We control for industry and country fixed effects, and five-year dummies, as well as global business cycle (world real GDP growth). We consider the following additional controls: log wage, the capital-to-wage ratio, and the changes in the capital-to-wage ratio at the industry level; the log GDP level, the log GDP per capita, and the measures of financial and trade globalization. Standard errors are clustered at the country-industry pair level. Additionally, the blue solid line shows the impulse response excluding H1N1 from pandemic episodes. While the coefficients estimates are similar to when considering all pandemics, the estimates are less precise given the number of pandemic episodes drops to less than a half (from 700 episodes to 314 episodes within the sample year and economies).

Figure A.2. Impact of Pandemic Case Number and Mortality on Robot Adoption
(Robot installation per 1000 employees in cumulative terms; T = pandemic year)

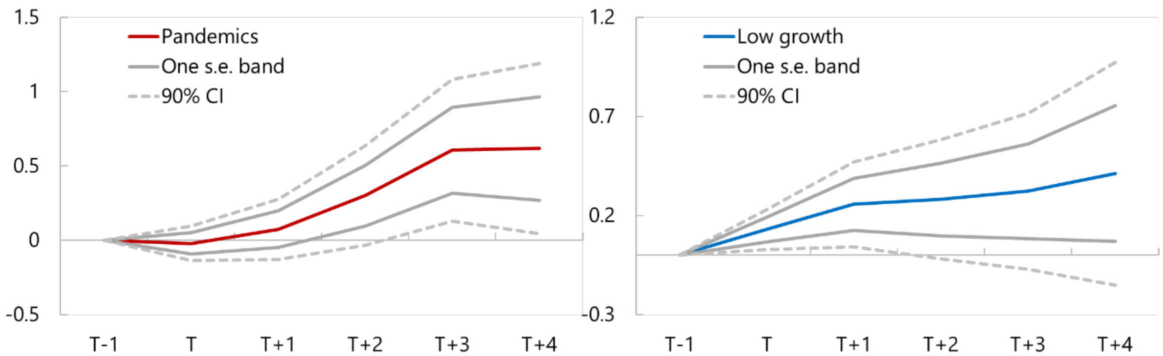
Case Number **Mortality**



Source: Authors.
Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). The estimates are based on: $R_{i,c,t+k} = \beta^k Fatailty_{c,t} + \theta^k X_{i,c,t} + Controls + \varepsilon_{i,c,t+k}$. The dependent variable R is new robot installations per 1000 employees in cumulative terms between t and $t+k$; $Fatality$ is the number of confirmed cases or deaths related to the pandemic in log; X denotes three lags of the dependent variable and the pandemic dummy. We control for industry and country fixed effects, and five-year dummies, as well as global business cycle (world real GDP growth). Standard errors are clustered at the country-industry pair level.

Figure A.3. Robot Adoption: Impact of Pandemics and Recessions

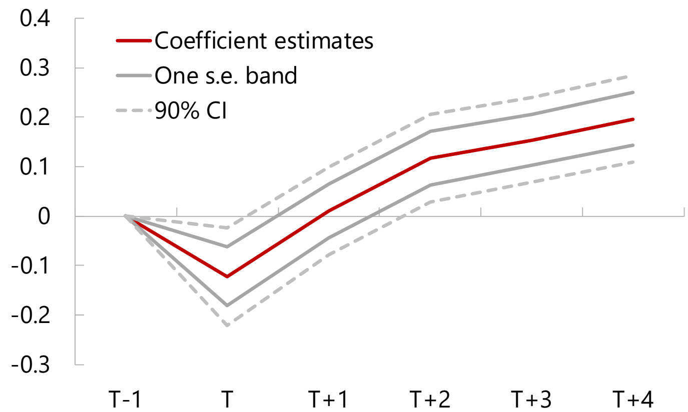
(Robot installation per 1000 employees in cumulative terms; T = pandemic/recession year)



Source: Authors.

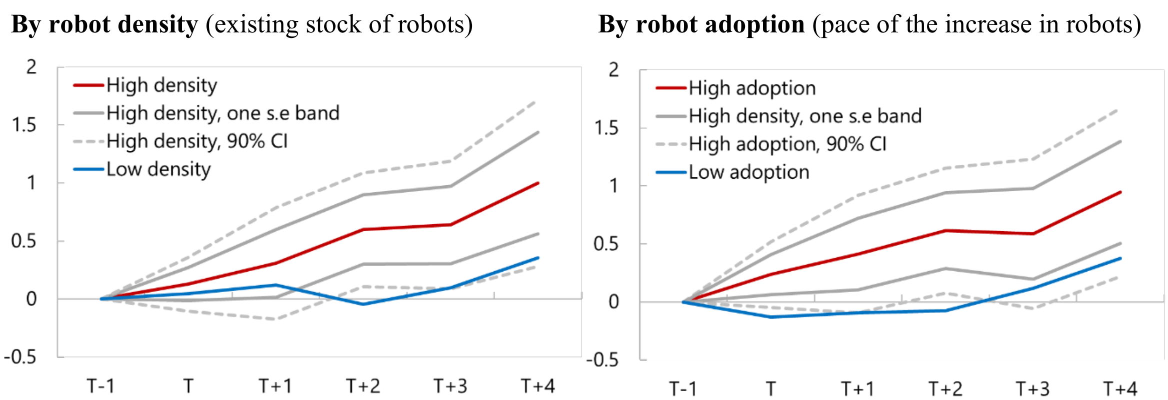
Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). The estimates are based on: $R_{i,c,t+k} = \beta^k D_{c,t} + \theta^k X_{i,c,t} + \varphi^k C_{c,t} + Controls + \varepsilon_{i,c,t+k}$. The dependent variable R is new robot installations per 1000 employees in cumulative terms; D is a dummy indicating pandemic years; C denotes a dummy indicating years with low growth; X denotes three lags of the dependent variable and the pandemic dummy. The estimation controls for industry and country fixed effects, five-year dummies, and global business cycle. Standard errors are clustered at the country-industry pair level.

Figure A.4. Robot Adoption in Log and Pandemics
(Robot installation per 1000 employees in cumulative terms; T = pandemic year)



Source: Authors.
Note: Impulse responses are estimated using a sample of 18 industries in 40 economies over the period 2000-2014, using local projection method (Jorda, 2005). The estimates are based on: $R_{i,c,t+k} = \beta^k D_{c,t} + \theta^k X_{i,c,t} + Controls + \varepsilon_{i,c,t+k}$. The dependent variable R is the log of the new robot installations per 1000 employees in cumulative terms between t and $t+k$; D is a dummy indicating pandemic years; X denotes three lags of the dependent variable and the pandemic dummy. We control for industry and country fixed effects, and five-year dummies, as well as global business cycle (world real GDP growth). Standard errors are clustered at the country-industry pair level.

Figure A.5. Changes in Net Gini Following Pandemics by Robotization Levels—Smooth Transitions
(Percentage points; T = pandemic year)



Source: Authors
Note: Impulse responses are estimated using a sample of 66 economies over the period 1993-2014, using local projection method (Jorda, 2005). The estimates are based on: $\Delta G_{c,t+k} = F(R_{it})[\beta_L^k D_{c,t} + \theta_L^k X_{i,c,t}] + [1 - F(R_{it})][\beta_H^k D_{c,t} + \theta_H^k X_{i,c,t}] + Controls + \varepsilon_{i,c,t+k}$. The dependent variable is the changes in net Gini in logs between t and $t+k$; D is a dummy indicating pandemic years; X denotes three lags of the dependent variable and the pandemic dummy; $F(R_{ct})$ is an indicator function of robot density or the pace of robot adoption, and the coefficient β_H^k captures the impact of a pandemic in the case of higher robot usage and β_L^k captures the impact in the case of the lower robot usage. The estimation controls for industry and country fixed effects, time dummies, and global business cycle. Standard errors are clustered at the country-industry pair level.

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