COVID-19, POLICY RESPONSES, AND INDUSTRIAL PRODUCTIVITY AROUND THE GLOBE

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ABSTRACT

We examine whether the COVID-19-induced policy responses by countries moderated the negative impact of the pandemic on industrial productivity. Using a panel of the 50 most affected countries by the pandemic, we show that the policy responses do not only help reduce the spread of COVID-19, but they also moderate its negative impact on industrial productivity and help steer countries back to their growth paths. We demonstrate that, in the absence of the pandemic, some of the policy responses (i.e., lockdowns, travel restrictions, etc.) would have reduced productivity. We further demonstrate that our estimates are robust when considering alternative specifications of our productivity model. Our study provides strong support for evidence-based policies and emphasizes, consistent with theoretical arguments, that an optimal policy mix is fundamental to steering economies back to their steady productivity growth paths when facing negative shocks.

Keywords: COVID-19; Novel coronavirus; Policy response indicators; Industrial productivity. **JEL Classifications: I18; E23.**

Article history:Received: May 27, 2021Revised: August 10, 2021Accepted: September 15, 2021Available Online : September 30, 2021

https://doi.org/10.21098/bemp.v24i3.1691

I. INTRODUCTION

The ongoing novel coronavirus (COVID-19) pandemic negatively impacted global financial markets, economies, and social welfare (see Sha and Sharma, 2020; Sharma and Sha, 2020, for an overview). To prevent further damages to economies and financial markets as well as to limit or eradicate the virus, policymakers implemented several policies, including lockdowns, cancellation of public events, face coverings, and fiscal and monetary measures (quantitative easing and fiscal stimulus packages), among others (Phan and Narayan, 2020; Iyke, 2020a). On the academic front, a growing body of research explores the degree of COVID-19's impact and whether these policy responses have been effective in terms of curtailing the negative impact of COVID-19 (see Devpura and Narayan, 2020; Haroon and Rizvi, 2020; Iyke, 2020b; Narayan, 2020a). Despite this, the literature has not explored the role of these policy responses in moderating the impact of COVID-19 on industrial productivity. This is perhaps due to the limited nature of industrial productivity data, which is not available at daily but at lower frequencies. To address this research gap, our study pools countries together to form a panel dataset and uses the resulting dataset to test our hypothesis that the policy responses moderated the impact of COVID-19 on industrial productivity.

Our hypothesis is motivated by the growing literature showing that extreme events like COVID-19 are associated with negative sentiments or extreme uncertainty that can reduce economic and financial activities (Behera and Rath, 2021; Chen et al., 2020; Haldar and Sethi, 2020; Iyke, 2020c, Iyke and Ho, 2021; Salisu and Akanni, 2020). The contagiousness of COVID-19 and the deaths associated with it caused panic and fear. From a theoretical perspective, the adverse information associated with the pandemic causes financial frictions by raising default risk and the cost of borrowing, which hurt investment and productivity (see Bernanke et al., 1999; Christiano et al., 2014). Similarly, the pandemic may also cause people to consume less to save for unexpected events (like infections and deaths), leading to demand shortages, surplus of goods, and low incentive to produce goods (see Basu and Bundick, 2017). The bad news associated with COVID-19 increases the option value of waiting, consistent with irreversibility of investment theory, which reduces productivity (see Bernanke, 1983). In turn, the conducive policy responses like expansionary monetary and fiscal policies, investment in vaccine development, and coordinated efforts to limit the spread of COVID-19, among others, will revitalize economies via boosting consumption and consumer confidence.

To test our hypothesis, we collect monthly data on industrial production indices, policy responses to the coronavirus pandemic, measures of COVID-19 (cases and deaths per million), and conditioning information on the 50 most affected economies by COVID-19 across the globe spanning the period from January 2020 to March 2021. Our main model regresses the annualized growth in the industrial production indices on the lag of COVID-19 related deaths per million, lag of policy response indicators, lag of the interaction of COVID-19 related deaths per million and the policy response indicators, and the lag of the conditioning information. In our robustness checks, we estimate various specifications of this model, including replacing COVID-19 related deaths per million with COVID-19 related cases per million, and using detrended and natural logarithm of industrial production as measures of industrial productivity.

Our estimations deliver the following findings. First, we show that the COVID-19-induced policy responses across these countries did not only help reduce the COVID-19 spread, but they also succeeded in moderating the negative impact of the pandemic on productivity and revert the economies to positive productivity growth paths. Second, in the absence of the pandemic, some of these policy responses-travel restrictions, bans on social events, lockdowns, etc.—would have hurt industrial productivity in these countries¹, suggesting that their implementation was timely to mitigate the destructive impact of COVID-19. Third, we demonstrate that these findings are robust using productivity models featuring COVID-19 related cases per million (in place of COVID-19 related deaths per million), and detrended and natural logarithm of industrial production (as measures of industrial productivity). Together, our findings provide support for evidence-based policy responses in times of crises. One implication is that, when negative shocks hit economies, measured policies such as packages to assist businesses, stimulus packages to households to smoothen consumption, small but significant interest rate cuts to reduce the cost of borrowing, etc. are necessary to keep them afloat. Such policies have both immediate and long-term positive spillovers and are social welfare enhancing.

Prior studies have assessed the impact of COVID-19 on various facets of economies and financial markets and whether policy responses mitigate the negative consequences of the pandemic have delivered positive outcomes. For example, COVID-19 caused: a decrease in the labor force participation rate (Bauer and Weber, 2021); a decrease in consumption and investment (Yu et al., 2020); and a contraction in output and credit (Barro et al., 2020; Choi, 2020; Liu et al., 2020). Past studies show that the COVID-19-induced policy responses have a mixed impact on various aspects of the economy. Ashraf (2020) shows that social distancing measures reduced COVID-19 cases and stock market returns, whereas awareness programs, quarantine, and testing policies increased stock market returns. Yang and Deng (2021) finds that government interventions like contact tracing, testing, and social distancing magnified the negative impact of the pandemic on stock returns. Baig et al. (2021) show declining liquidity and stability of stock markets following the implementations of COVID-19 induced lockdowns and other restrictions. Bannigidadmath et al. (2021) demonstrate that COVID-19 related government policies generally have a negative impact on stock markets. Feng et al. (2021) find that the various policies implemented by governments, including public awareness campaigns and restrictions on internal movements reduced COVID-19 induced exchange rate volatility. Similarly, Zaremba et al. (2021) show that government interventions significantly decreased sovereign bond volatility.

Padhan and Prabheesh (2021) provide an extensive survey of the literature. By and large, no study assesses whether the policy responses by countries succeeded in moderating the negative impact of the pandemic on industrial productivity. Our study contributes to the literature in this regard by showing that the policy responses have been effective in moderating COVID-19's impact on productivity. Our analyses also contribute to the literature on the optimal policies in times of

¹ This is true even for economic support packages in normal times because they do not encourage hard work but shift capital to unproductive sectors of the economy.

crises (see Assenza *et al.*, 2020; Kahn and Wagner, 2021; Mitman and Rabinovich, 2020; Moser and Yared, 2020). It shows that an optimal policy mix (fiscal, monetary, and other policies) is necessary to overcome a crisis. The paper proceeds as follows. In Section II, we detail our data and methodology. Section III presents the results, while Section IV concludes the paper.

II. DATA AND METHODOLOGY

A. Data

In this study, we use monthly data of 50 countries severely impacted by the COVID-19 pandemic over the period from January 2020 to March 2021. These 50 countries are listed in Panel B of Table 1. Note that some countries have missing observations on some variables in certain months. Hence, our panel data is unbalanced. We use the annualized growth rate of industrial production indices as our dependent variable (see Panel A of Table 1, for the computation of this variable). The industrial production indices are sourced from the from Bank of Indonesia. We consider the following three groups of datasets as our explanatory variables. The first group of explanatory variables include five proxies of policy response indicators to the pandemic, namely stringency index, stringency legacy index, government response index, containment and health index, and economic support index. Data on all these policy response indices are downloaded from the Blavatnik School of Government database.

The second group of explanatory variables include two measures of the COVID-19 pandemic, namely total number of cases (per million) and total number of deaths (per million) for each country. These COVID-19 measures are sourced from the online published database, namely Our World in Data (see www.ourworldindata.org). The final set of variables used in this study are the following four control variables, namely short-term interest rates, money supply (M2), inflation rate (measured as the growth rate of consumer price index), and stock price. Detail description of all variables considered for this study is given in Panel A of Table 1.

Table 1. List of Variables and the Selected Countries

This table shows the list of variables—their short, full names, and definitions, where applicable—the sources from which we gathered data on them, and the selected countries.

Panel A: List of Variables					
Variable	Full Name	Source(s)			
Industrial productivity					
variables					
IP	Industrial production index	Bank of Indonesia			
Δ IP	Annualised growth rate of IP, which we calculated as	Authors'			
	$\Delta IP_{i,t} = [ln(IP)_{i,t}/ln(IP)_{i,t-1}]^* 100$ for IP <i>i</i> in period <i>t</i> .	computation			
dIP	Detrended IP, which involves regressing IP on the trend	Authors'			
	and subtracting the best fit line from IP (or extracting	computation			
	the error term from the regression).	_			

Panel A: List of Variables						
Variable	Full Na	me	Source(s)			
COVID-19 variables						
TC	Total COVID-19 cas	ses per million	Our World in Data			
TD	Total COVID-19 dea	ths per million	Our World in Data			
Policy response variables						
SI	Stringency Index, which me	asures the strictness of	Blavatnik School of			
	lockdown p	olicies.	Government			
SL	Stringency Legacy Index, w	hich approximates the	Blavatnik School of			
	intuition of the original version	n of the Stringency Index	Government			
CT.	and measures the strictness	of lockdown policies.				
GI	Government Response Inde	x, which measures the	Blavatnik School of			
CU	variation of government resp	onse over all indicators.	Government			
СП	Containment and Health Ir	aligios by combining	Blavatnik School of			
	moosures of lookdown clor	oncies by combining	Government			
	with others like contact trac	ing and testing policy				
	investments in vaccine inves	tments and short-term				
	healthcare inve	estments.				
ES	Economic Support Inde	x, which measures	Blavatnik School of			
	governments' economic supp	port like debt relief and	Government			
	income support (stimulus pa	ckages) for households				
	and businesses impact	ed by COVID-19.				
Conditioning variables						
M2	Money Supply (bi	CEIC				
$\Delta M2$	Annualised growth rate of M2	Authors'				
ID	$\Delta M2_{i,t} = [ln(M2)_{i,t}/ln(M2)_{i,t-1}]^{*1}$	computation				
IK	Short-term inte	erest rate	Bloomberg and			
CP	Consumer price in	day inflation	CEIC Bank of Indonesia			
SP	Stock price	index	Bloomborg and			
51	Stock plice	lindex	CFIC			
ASP	Annualised growth rate of SP	which we calculated as	Authors'			
201	$\Delta SP. = [ln(SP), /ln(SP),]*1($)0 for SP i in period t .	computation			
	Papal R: Ca	intrioc	1			
Argontina	Coorgia	Malaysia	Sorbia			
Austria	Germany	Mexico	Slovakia			
Bangladesh	Hungary	Morocco	South Africa			
Belarus	India	Netherlands	Spain			
Belgium	Indonesia	Pakistan	Sweden			
Brazil	Iran (Islamic Republic of)	Panama	Switzerland			
Bulgaria	Iraq	Peru	Turkey			
Canada	Israel	Philippines	Ukraine			
Chile	Italy	Poland	United Arab			
	5		Emirates			
Colombia	Japan	Portugal	United Kingdom			
Czechia	Jordan	Romania	United States of			
			America			
Ecuador	Kazakhstan	Russian Federation	_			
France	Lebanon	Saudi Arabia	_			

Table 1. List of Variables and the Selected Countries (Continued)

B. Methodology

Our approach to examining the hypothesis that the conducive policy responses like expansionary monetary and fiscal policies, investment in vaccine development, and coordinated efforts to limit the spread of COVID-19, among others, will revitalize economies via boosting consumption and consumer confidence is as follows. We first examine whether the industrial productivity of the panel of 50 countries are significantly negatively affected by the COVID-19 pandemic by employing the following regression model:

$$\Delta IP_{i,t} = \alpha_0 + \beta_1 lnTD_{i,t-1} + \delta X'_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

Next, to examine whether the policies adopted during the pandemic eased the negative effects of COVID-19 on industrial productivity, we estimate the following regression model:

$$\Delta IP_{i,t} = \alpha_1 + \varphi_1 lnTD_{i,t-1} + \varphi_2 lnPol_{i,t-1} + \varphi_3 lnTD_{i,t-1} * lnPol_{i,t-1} + \gamma X'_{i,t-1} + \epsilon_{i,t}$$
(2)

In Equations (1) and (2), $\Delta IP_{i,i}$ denotes an annualized growth form of industrial production of country *i* at time *t* and *lnTD* denotes the total number of deaths per million due to the COVID-19 pandemic. $X_{i,i}$ represents four control variables, namely change in money supple ($\Delta M2$), short-term interest rate (*IR*), inflation rate (*CP*), and stock returns (ΔSP). The indicator *lnPol* denotes policy response variables, namely stringency index (*lnSI*), stringency legacy index (*lnSL*), government response index (*lnGI*), containment and health index (*lnCH*), and economic support index (*lnES*). The operator *ln* denotes that variables considered Equations (1) and (2) are in natural logarithm form and since we have five measures of policy response, we estimate Equation (2) five times by considering each measure at a time in the regression model. Additionally, we estimate Equations (1) and (2) using the fixed-effects estimator (by controlling year and country fixed effects) and cluster standard errors at the country level.

III. MAIN FINDINGS

This section is organized into three parts. In the first part, we discuss some key statistical features of the data. The second part of the section explains the findings from the panel regression models discussed in Section II. In the final part of this section, we discuss the robustness check of our main findings.

A. Preliminary Results

We begin by reporting in Table 2 selected descriptive statistics for variables used in this study. Descriptive statistics are reported for raw variables in Panel A, whereas Panel B reports descriptive statistics of variables in the form considered in regression models, mainly in natural logarithm or growth form. We report mean, maximum and minimum values, and Standard Deviation (SD) for all variables in columns 2 to 5, respectively. In the final column, we report the number of observations for each variable. We note that the mean growth rate of industrial production is negative during the pandemic, while for other variables considered in the study, the mean is found to be positive. We also noted an average of 11,983 positive COVID-19 cases and 300 deaths (per million) are recorded during the pandemic for the panel of 50 countries. Additionally, for all five policy response indicators (namely *SI*, *SL*, *GI*, *CH*, and *ES*) and four control variables (*M2*, *IR*, *CP*, and *SP*) positive mean are reported.

Table 2. Summary Statistics

This table shows summary statistics of the variables. These statistics are the mean, maximum, minimum, Standard Deviation (SD), and total observations. Δ denotes annualized changes (growth) in a variable. *In* denotes the natural logarithm operator. Panels A and B contain summary statistics of the raw and transformed variables, respectively, computed for a panel of 50 countries over the sample period from January 2020 to March 2021. Note that M2 is in millions in Panel A.

Panel A: Raw Variables								
Variable	Mean	Maximum	Minimum	SD	Observations			
IP	110.427	451.720	10.943	45.555	528			
TD	296.672	1904.895	0.000	396.553	687			
TC	11983.888	115368.576	0.000	17912.023	691			
SI	58.972	100.000	0.000	25.795	700			
SL	64.662	100.000	0.000	25.626	700			
GI	54.635	87.760	0.000	21.614	698			
CH	55.321	89.580	0.000	21.718	700			
ES	50.143	100.000	0.000	32.030	697			
M2	706.535	31300.200	-0.442	3884.719	610			
IR	2.810	40.000	-0.842	4.945	602			
СР	5.653	157.859	-2.890	17.138	745			
SP	35567.432	1904324.000	21.000	178697.985	684			
		Panel B: Transf	ormed Variable	S				
ΔIP	-0.062	202.153	-189.715	17.280	478			
lnTD	4.077	7.553	0.000	2.388	687			
lnTC	7.197	11.656	0.000	3.348	691			
lnSI	3.963	4.605	1.022	0.690	675			
lnSL	4.088	4.605	1.273	0.606	675			
lnGI	3.869	4.475	0.445	0.727	682			
lnCH	3.892	4.495	0.582	0.691	684			
lnES	4.064	4.605	2.526	0.413	557			
$\Delta M2$	1.136	135.751	-143.630	12.818	563			
ΔSP	0.330	49.793	-60.176	8.972	633			

Next, we read the panel unit root test results from Table 3. More specifically, we test the null hypothesis of "panel unit root" using the Levin, Liu, and Chu (LLC, 2002) and Im, Pesaran, and Shin (IPS, 2003) panel unit root tests. We find that, irrespective of the tests used, our results are consistent for all variables. More specifically, we reject the null hypothesis of panel unit root at 1% significance level for all variables. This indicates, all variables considered in the panel regression models (discussed earlier in Section II) follow a stationary process.

Table 3. Unit Root Test Results

This table reports the unit root test results. We test for unit roots using the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests. Panels A and B considered constant only and constant and trend, respectively, in the test regressions. *p*-values are in the parentheses.

	Panel A:	Panel A: Constant		ant and Trend
Variable	LLC (<i>p</i> -value)	IPS (<i>p</i> -value)	LLC (<i>p</i> -value)	IPS (p-value)
ΔΙΡ	-19.243	-10.239	-17.068	-4.599
	(0.000)	(0.000)	(0.000)	(0.000)
lnTD	-78.402	-45.326	-83.341	-33.937
	(0.000)	(0.000)	(0.000)	(0.000)
lnTC	-67.057	-51.112	-2.470	-27.849
	(0.000)	(0.000)	(0.007)	(0.000)
lnSI	-64.278	-37.264	-111.159	-47.369
	(0.000)	(0.000)	(0.000)	(0.000)
lnSL	-56.170	-31.403	-98.623	-47.707
	(0.000)	(0.000)	(0.000)	(0.000)
lnGI	-61.200	-47.000	-185.675	-74.296
	(0.000)	(0.000)	(0.000)	(0.000)
lnCH	-48.689	-36.276	-64.500	-37.294
	(0.000)	(0.000)	(0.000)	(0.000)
lnES	-9.531	-4.250	-15.742	-3.496
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta M2$	-15.417	-13.704	-20.760	-12.274
	(0.000)	(0.000)	(0.000)	(0.000)
IR	-33.784	-23.034	-38.171	-14.690
	(0.000)	(0.000)	(0.000)	(0.000)
СР	-4.191	-2.862	-4.216	1.196
	(0.000)	(0.002)	(0.000)	(0.884)
ΔSP	-25.622	-16.579	-23.421	-11.813
	(0.000)	(0.000)	(0.000)	(0.000)

B. Empirical Findings

First, we discuss results reported in Table 4, which we have obtained by estimating Equation (1). Here, we examine whether COVID-19 has a negative effect on industrial productivity of the panel of 50 countries. We estimate Equation (1) five times and report respective results in columns 2 – 6. In model 1, we regress ΔIP on one period lag of *lnTD*. This is a baseline model, which contains no control variables. In the remaining four models, we introduce each control variable (namely $\Delta M2$, *IR*, *CP*, and ΔSP) one by one to check the robustness of our findings. Overall, we find that COVID-19 pandemic (proxied using one period lag of *lnTD*) has a statistically significant and negative effect on productivity in 3/5 models. In models (1) and (5), we find that *lnTD* is statistically insignificant, however the sign is still negative. Thus, we conclude that the industrial productivity of the panel of 50 countries declined due to the COVID-19 pandemic. This is supported by Figure 1, which shows that industrial productivity experienced a decline as the economies recorded substantial growth in COVID-19 deaths. Productivity continued to fall,

recording a mean growth rate of -27% by April 2020, before climbing back to and above the baseline as policymakers bring down COVID-19 deaths towards zero through restrictive measures, extensive awareness campaigns, investment in hospital facilities, etc.

Variable	(1)	(2)	(3)	(4)	(5)
Constant	3.966	6.633	7.581	7.559	4.710
	(0.124)	(0.098)	(0.057)	(0.053)	(0.168)
lnTD _{it-1}	-1.051	-1.659	-1.624	-1.630	-0.942
	(0.124)	(0.097)	(0.080)	(0.090)	(0.201)
$\Delta M2_{it-1}$		0.010	0.013	0.012	0.014
		(0.168)	(0.152)	(0.126)	(0.040)
IR _{it-1}			-0.446	-0.438	-0.557
			(0.246)	(0.261)	(0.131)
CP _{it-1}				-0.190	1.180
				(0.846)	(0.245)
ΔSP_{it-1}					0.157
					(0.081)
R ²	0.337	0.335	0.342	0.342	0.476
Adjusted R ²	0.248	0.236	0.236	0.234	0.387

Table 4. Impact of COVID-19 on Industrial Productivity

This table reports the impact of COVID-19 on productivity growth across countries. We regress industrial productivity (measured by annualized IP growth) on lags of *ln*TD, Δ M2, IR, CP, and Δ SP. Coefficients and *p*-values are outside and inside parentheses, respectively.

Figure 1. Industrial Productivity and Growth in COVID-19 Death Dynamics

This figure shows the behavior of mean industrial productivity and mean growth in total COVID-19 deaths per million people for a panel of 50 countries over the sample period from January 2020 to March 2021.



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Next, we examine whether the different policies adopted during the pandemic helped eased the negative effects of COVID-19 on industrial productivity by estimating Equation (2). These results are reported in Table 5. Here we consider five different policy response indicators, (namely *SI*, *SL*, *GI*, *CH*, and *ES*), and report results in columns 2 - 6, respectively. Our findings are as follows. First, we note that *ln TD*, which proxies the COVID-19 pandemic has a negative and statistically significant effect on productivity. Second, we observe that *ln POL*, which captures the effect of the policy responses during the pandemic also has a negative and statistically significant effect on productivity. Our findings are consistent with the use of 4/5 different policy response indicators. The only exception is model 5, whereby we use *ES* as a proxy for the policy response indicator. It is important to note that the *ES* index measures governments' economic support like debt relief and income support (stimulus packages) for households and businesses impacted by the pandemic and, therefore, the effect of such policies will have a positive effect on countries productivity.²

In the remaining four models, the negative and statistically significant effect of policy responses on industrial productivity is not surprising because these policy response indicators mostly capture very restrictive measures—such as, lockdowns, cancellation of public events, restrictive movements, face covering, and travel bans amongst others—which indeed will not help in boosting the productivity of a country but will help in containing the spread of the virus and should curtail the negative effects of COVID-19 on productivity. Therefore, to

² For details, see https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

empirically ascertain that the negative effects of the pandemic on productivity can be moderated by imposing different policies, we have included an interaction of COVID-19 measure, *ln TD*, with the policy response indicators, *ln POL*, in Equation (2). We find that the effect of the interaction variable (lnTD*lnPOL) is positive and statistically significant on productivity of the panel of 50 countries in 4/5 models. Thus, our findings imply that imposing such restrictive policies during the pandemic does not only help reduce the spread of the virus but also helps dilute the negative effects of the pandemic on countries industrial productivity. The only exception is model 5, where the sign of the interactive variable is negative. As we mentioned earlier, the policy indicator, ES index, measures governments' economic support like debt relief and income support (stimulus packages) for households and businesses impacted by the pandemic, which means that it should cushion productivity against the negative COVID-19 shock.

Variable	(1)	(2)	(3)	(4)	(5)
Constant	38.467	39.151	37.927	41.361	-39.108
	(0.007)	(0.002)	(0.000)	(0.000)	(0.002)
nTD _{it-1}	-14.354	-17.736	-16.000	-16.376	10.944
	(0.007)	(0.012)	(0.000)	(0.002)	(0.007)
nPOL _{it-1}	-7.794	-7.723	-8.060	-8.810	11.736
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
lnTD _{it1} *lnPOL _{it1}	3.102	3.809	3.612	3.683	-3.108
	(0.005)	(0.010)	(0.001)	(0.001)	(0.003)
M2 _{it-1}	0.017	0.016	0.019	0.019	0.020
	(0.041)	(0.052)	(0.034)	(0.040)	(0.124)
R _{it-1}	-0.560	-0.523	-0.700	-0.681	0.023
	(0.103)	(0.125)	(0.080)	(0.085)	(0.936)
CP _{it-1}	1.040	0.903	1.209	1.168	0.172
	(0.319)	(0.399)	(0.227)	(0.247)	(0.883)
ΔSP_{it-1}	0.081	0.079	0.100	0.103	0.097
	(0.350)	(0.373)	(0.240)	(0.232)	(0.352)
χ ²	0.498	0.497	0.494	0.496	0.467
Adjusted R ²	0.408	0.407	0.404	0.407	0.357

Table 5. The Role of Policy Responses

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C. Robustness Checks

In this section, we conduct robustness checks of our earlier reported empirical findings. Our approach is twofold. First, we use a different proxy to capture the effects of the COVID-19 pandemic. More specifically, we use the total number of cases (per million, *ln TC*) instead of *ln TD* in Equation (2) as a proxy for the

pandemic. These results are reported in Table 6. The remaining variables considered in the model remain same, except instead of interacting *ln TD* with *ln POL*, we now consider *ln TC*ln POL* to capture the combined effects of the COVID-19 pandemic and policy implementations during the pandemic. Our overall findings remain same, and we do conclude that implementing different policies during the pandemic helps in reducing the negative effects of COVID-19 on industrial productivity of the panel of 50 countries.

Table 6. Using Total Cases per Million as a Measure of COVID-19

This table shows empirical evidence regarding whether policy responses moderated the impact of COVID-19 (measured in terms of the total number of cases per million) on productivity growth across countries. We regress productivity (measured by annualized IP growth) on lags of lnTC, lnPOL, lnTC*lnPOL, Δ M2, IR, CP, and Δ SP. In Columns (1), (2), (3), (4), and (5), we include policy response indicators SI, SL, GI, CH, and ES, respectively. Coefficients and *p*-values are outside and inside parentheses, respectively.

** * 1 1	(1)	(0)	(2)	(4)	(=)
Variable	(1)	(2)	(3)	(4)	(5)
Constant	35.311	37.851	35.269	38.185	-65.307
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnTC _{it-1}	-7.092	-9.353	-7.298	-7.494	9.852
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
<i>ln</i> POL _{it-1}	-7.680	-7.897	-8.331	-8.889	15.909
	(0.030)	(0.020)	(0.002)	(0.003)	(0.001)
<i>ln</i> TC _{it-1} * <i>ln</i> POL _{it-1}	1.605	2.070	1.752	1.779	-2.369
	(0.001)	(0.003)	(0.000)	(0.000)	(0.002)
$\Delta M2_{it-1}$	0.018	0.018	0.019	0.019	0.016
	(0.001)	(0.007)	(0.001)	(0.001)	(0.001)
IR _{it-1}	-0.617	-0.594	-0.744	-0.734	-0.110
	(0.100)	(0.116)	(0.084)	(0.086)	(0.764)
CP _{it-1}	1.130	1.009	1.271	1.258	0.290
	(0.262)	(0.319)	(0.189)	(0.195)	(0.801)
ΔSP_{it-1}	0.093	0.091	0.113	0.116	0.116
	(0.274)	(0.299)	(0.186)	(0.176)	(0.273)
R ²	0.491	0.492	0.488	0.489	0.463
Adjusted R ²	0.400	0.401	0.398	0.399	0.352
Adjusted R ²	0.400	0.401	0.398	0.399	0.352

Next, we consider using two alternative measures of our dependent variable, ΔIP . Motivated by the literature (see Giordani, 2004; Bjørnland and Leitemo, 2009), instead of using annualized growth rate of industrial production, we use linear detrended *IP* (*dIP*) and the natural logarithm of *IP* (*lnIP*) as dependent variable in Equation 2, to check the consistency of our results.³ Results obtained using detrended *IP* and natural logarithm of *IP* are reported in Tables 7 and 8, respectively. We find

³ This is slightly different from differencing the natural logarithm of IP, although both entails removing a trend in the IP series. When detrending IP, we regress IP on the trend and subtract the best fit line from IP (or extract the error term from the regression). Differencing IP entails subtracting the previous value of IP (IP_{I-1}) from the current value (IP_{I}). Differencing removes trends but produces non-white noise error terms, whereas detrending by least squares introduces autocorrelations if IP follows a random walk. For a detailed discussion, refer to Chan, Hayya, and Ord (1977).

that irrespective of the use of different measures of *IP*, our main conclusion does not change. That is, the impact of the pandemic and policy response indicators on productivity remains negative and statistically significant. Besides, the interactive variable, *ln TD*ln POL*, is found to be positive and statistically significant, which again implies that the implementation of different policies during the pandemic curtailed the negative effects of COVID-19 on countries industrial productivity.

Table 7. Using Detrended IP as a Measure of Industrial Productivity

This table shows empirical evidence regarding whether policy responses moderated the impact of COVID-19 on productivity growth across countries. We regress productivity (measured by detrended IP, *d*IP) on lags of *ln*TD, *ln*POL, *ln*TD**ln*POL, Δ M2, IR, CP, and Δ SP. In Columns (1), (2), (3), (4), and (5), we include policy response indicators SI, SL, GI, CH, and ES, respectively. Coefficients and *p*-values are outside and inside parentheses, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
Constant	0.385	0.378	0.299	0.327	-0.136
	(0.040)	(0.032)	(0.048)	(0.064)	(0.457)
<i>ln</i> TD _{it-1}	-0.117	-0.143	-0.144	-0.127	0.018
	(0.084)	(0.113)	(0.018)	(0.058)	(0.729)
<i>ln</i> POL _{it-1}	-0.087	-0.083	-0.069	-0.075	0.044
	(0.010)	(0.007)	(0.016)	(0.026)	(0.401)
lnTD _{it-1} *lnPOL _{it-1}	0.026	0.031	0.033	0.029	-0.008
	(0.048)	(0.082)	(0.008)	(0.036)	(0.582)
$\Delta M2_{it-1}$	2.E-04	2.E-04	2.E-04	2.E-04	2.E-04
	(0.076)	(0.067)	(0.045)	(0.066)	(0.136)
IR _{it-1}	-4.E-04	-1.E-04	-0.002	-0.001	0.004
	(0.818)	(0.944)	(0.433)	(0.507)	(0.022)
CP _{it-1}	-5.E-05	-0.001	0.003	0.002	-0.007
	(0.995)	(0.921)	(0.765)	(0.793)	(0.559)
ΔSP_{it-1}	1.E-04	1.E-04	1.E-04	2.E-04	-2.E-04
	(0.917)	(0.920)	(0.903)	(0.861)	(0.905)
R ²	0.825	0.824	0.823	0.823	0.833
Adjusted R ²	0.793	0.792	0.791	0.791	0.797

Table 8.

Using the Natural Logarithm of IP as a Measure of Industrial Productivity

This table shows empirical evidence regarding whether policy responses moderated the impact of COVID-19 on productivity growth across countries. We regress productivity (measured by the natural logarithm of IP, *ln*IP) on lags of *ln*TD, *ln*POL, *ln*TD**ln*POL, Δ M2, IR, CP, and Δ SP. In Columns (1), (2), (3), (4), and (5), we include policy response indicators SI, SL, GI, CH, and ES, respectively. Coefficients and *p*-values are outside and inside parentheses, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
Constant	5.049	5.043	4.963	4.992	4.532
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnTD _{it-1}	-0.117	-0.143	-0.144	-0.127	0.018
	(0.084)	(0.113)	(0.018)	(0.058)	(0.729)
<i>ln</i> POL _{it-1}	-0.087	-0.083	-0.069	-0.075	0.044
	(0.010)	(0.007)	(0.016)	(0.026)	(0.401)

(Continued)						
Variable	(1)	(2)	(3)	(4)	(5)	
<i>ln</i> TD _{it-1} * <i>ln</i> POL _{it-1}	0.026	0.031	0.033	0.029	-0.008	
	(0.048)	(0.082)	(0.008)	(0.036)	(0.582)	
$\Delta M2_{it-1}$	2.E-04	2.E-04	2.E-04	2.E-04	2.E-04	
	(0.076)	(0.067)	(0.045)	(0.066)	(0.136)	
IR _{it-1}	-4.E-04	-1.E-04	-0.002	-0.001	0.004	
	(0.818)	(0.944)	(0.433)	(0.507)	(0.022)	
CP _{it-1}	-5.E-05	-0.001	0.003	0.002	-0.007	
	(0.995)	(0.921)	(0.765)	(0.793)	(0.559)	
ΔSP_{it-1}	1.E-04	1.E-04	1.E-04	2.E-04	-2.E-04	
	(0.917)	(0.920)	(0.903)	(0.861)	(0.905)	
R ²	0.830	0.829	0.828	0.828	0.837	
Adjusted R ²	0.799	0.798	0.797	0.797	0.803	

Table 8. Using the Natural Logarithm of IP as a Measure of Industrial Productivity (Continued)

IV. CONCLUSION

The theory suggests that a negative shock like the COVID-19 would reduce industrial productivity around the globe, and in fact empirical evidence supports this prediction. The pandemic has negatively impacted productivity around the world. In attempt to prevent COVID-19 from further spreading and to tackle its negative ramifications on economies, policymakers introduced various policy measures including lockdowns, bans on public gatherings and events, restrictive movements, face covering, border closures, stimulus packages, interest rate reductions, among others. Prior studies have assessed whether such policy responses mitigated the negative consequences of the pandemic on various macroeconomic and financial activities. However, we have little knowledge regarding whether the policy responses moderated the negative impact of COVID-19 on industrial productivity, in particular.

Our study addresses this research gap by regressing industrial productivity on COVID-19 and policy response indicators and the interaction of these indicators, considering a panel of the 50 most affected countries by the pandemic. We unearth the following findings. First, separately, the pandemic and the policy responses reduced industrial productivity. Absent the pandemic, some of the policy responses (i.e., lockdowns, bans on public gatherings and events, restrictive movements, face covering, border closures, etc.) hurt productivity in these countries and vice versa. Second, these policy responses do not only help reduce the COVID-19 spread, but they also succeed in moderating the negative impact of the pandemic on productivity and revert the economies to a positive productivity growth path. Third, we demonstrate that these findings are robust to, among others, the proxies of industrial productivity, COVID-19, and the policy responses. Our findings provide support for evidence-based policy responses in times of crises. An implication is that, when negative shocks hit economies, measured policies such as packages to assist businesses, stimulus packages to households to maintain smooth consumption, small but significant interest rate

cuts to reduce the cost of borrowing, etc. are necessary to keep them afloat. Such policies have both immediate and long-term positive spillovers and are social welfare enhancing. From a theoretical standpoint, our findings re-echo the need for an optimal policy mix to maintain economies on a steady growth path as previously documented in the macroeconomic policy literature.

Acknowledgement: An earlier version of this paper was presented on July 2, 2021 at the International Economic Association Online World Congress on the theme "COVID-19 and Monetary Policy". This session was sponsored by Bank Indonesia and jointly organised by Bank Indonesia and the Asia-Pacific Applied Economics Association. Helpful comments and suggestions from conference participants and two reviewers of BMEB are duly acknowledged.

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