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Abstract

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JEL Classification: E24, E32, E52

Keywords: Fiscal policy, COVID-19, multipliers, high-frequency data

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The Effects of Fiscal Measures During COVID-19[•]

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I. Introduction

Beginning in early 2020, countries worldwide launched wide-scale fiscal support measures to mitigate the unprecedented output losses from the COVID-19 pandemic (IMF, 2020). While it is understood that fiscal policies deployed during the pandemic provided timely and critical support to households, businesses, and economies overall, the effect of these measures on economic activity, unemployment, and consumer, business, and investor confidence, remains an open question. Estimating the measures' economic effects is of paramount importance for policymakers, as they assess how much support is needed in a context of dwindling fiscal space.

A key challenge is identifying fiscal shocks in the data. Previous research used narrative or structural time series (SVAR) methods to isolate unanticipated, exogenous innovations to government spending or revenue. A problem with these approaches in our context is that they have typically been applied to annual or quarterly data, and are thus less suited if the question is to assess the effect of fiscal policy during COVID-19. Our approach instead relies on daily data of announced fiscal measures and combines the high-frequency identification (HFI) method of Gertler and Karadi (2015) applied to fiscal announcements (Auerbach and Gorodnichenko, 2016) with the narrative approach of Romer and Romer (2010), Ramey (2011), and Alesina et al. (2014).

Our paper has three main goals. The first is to quantify the average effect of fiscal policy announcements on economic activity across countries. For this purpose, we assemble a novel daily database of announcements regarding the fiscal policy interventions deployed across 52 countries throughout 2020.[1] We collect information on the date of announcement and implementation, the

[1] We focus on the 52 countries for which data on industrial production and PMI manufacturing is available.

authorizing institution (e.g., fiscal authority, monetary authority, or a regulatory authority), the policy tool (e.g., credit guarantee vs. public investment), and the magnitude of the fiscal measure. At a daily frequency it is unlikely that fiscal announcements react to developments in the economy, which limits concerns about reverse causality. To further address endogeneity concerns, we purge the daily announcements from lagged daily measures of activity indicators that have been recently used to track the economic effects of the COVID-19 crisis—specifically Nitrogen Dioxide (NO_2) emissions, international and domestic flights, mobility indicators, and daily financial variables that can help capture expectations regarding future economic activity.

Our results suggest that fiscal announcements are associated with a persistent increase in stock market indicators and, consistent with theory and evidence in Auerbach and Gorodnichenko (2013), with an appreciation of the domestic currency *vis-à-vis* the US dollar. At weekly frequencies, we also find that fiscal announcements are followed by an increase in the OECD economic tracker indicator of economic activity.

We then turn to effect of fiscal measures on more standard indicators of economic activity—industrial production indices, manufacturing Purchasing Managers' Indices (PMIs), unemployment rates, the OECD's Composite Leading Indicators (CLI) for confidence, and sovereign credit default swap (CDS) spreads—available at the monthly frequency. For this purpose, and following Gertler and Karadi (2015), we aggregate the daily shocks into monthly average shocks. The results suggest that fiscal policy announcements implemented during COVID-19 have had, on average, a significant effect on economic activity. In particular, we find that a fiscal shock of one percent of GDP increases industrial production by 0.25 percent. In terms of the effect on GDP, back-of-the envelope calculations suggests that this effect is equivalent to a fiscal multiplier of about 0.2 for the entire sample (on average).[2]

The effect of fiscal announcements is also significant on PMI, unemployment, confidence indicators, and sovereign CDS spreads: a one percent of GDP fiscal announcement leads to an increase in the PMI by 0.38 percent, a reduction in the monthly unemployment rate by 0.06 percentage points, a boost of the OECD Composite Leading Indicators (CLI) by about 0.1 percent, and a reduction in the sovereign CDS spread by 0.05 basis points.

The second goal of the paper is to assess whether the effect of (different types of) fiscal measure varies across countries depending on structural characteristics (such as the level of development, trade openness, the level of public debt before the crisis) and across time depending on the severity of the pandemic and lockdown restrictions. The results on country characteristics are consistent with previous findings of the literature (e.g., Nickel and Tudyka, 2014; Ilzetzki et al. 2013) and suggest that effects are larger for the advanced economies in our sample and in countries with lower public debt going to the crisis. In contrast, probably because of limited cross-country heterogeneity in trade openness and exchange rate regimes, we do not find statistically significant differential effects along these two dimensions.

The third goal of this paper is to examine whether the effect of fiscal stimulus measures varies depending on the type of measure used. For this, we follow the narrative approach (Romer and Romer, 2010; Ramey 2011; Alesina et al. 2014) and read the record of each of the policy measures implemented and classify them in: (i) demand support measures; (ii) emergency lifelines measures; (iii) above-the-line; and (iv) below-the-line measures. The results show that, on average,

[2] The results are based on the historical relationship between industrial production and GDP.

emergency lifelines measures—such as loans to firms and households, umbrella guarantees and equity injections (which form the bulk of below-the-line measures)—have been more effective in boosting economic activity during COVID-19 than demand-support measures—such as tax cuts or payment deferrals, cash transfers and unemployment insurance. However, these results mask significant heterogeneity depending on the state of pandemic "cycle". In particular, emergency lifeline measures appear more effective when containment is high and social mobility is low. This is consistent with the idea that when supply constraints are high, emergency lifelines—such as loans to firms or credit guarantees—provide much-needed liquidity support to firms and businesses so that they may continue to operate. On the other hand, demand-support measures appear more effective when containment measures are being eased and supply constraints are lower. In other words, measures such as public investment are more likely to feed into domestic demand when supply-side restrictions have been relaxed and spending opportunities are ample.

The rest of the paper is structured as follows. We briefly survey the literature in Section II. Section III describes the data and Section IV presents some stylized facts on the fiscal measures. Section V discusses the empirical methodology and the results. Section VI concludes.

II. Literature Review

The literature examining the effects of fiscal spending relies on two main approaches for identification. The first uses Structural Vector Autoregression (SVAR) techniques developed by Blanchard and Perotti (2002), where identification is achieved by assuming that government spending is pre-determined within the quarter, using a standard Cholesky decomposition with government spending ordered first. The second identification strategy uses the narrative approach (Romer and Romer 2010, Devries et al. 2011) to identify the size, timing, and objective of fiscal shocks. Uses of the narrative approach are abundant in the literature, from narrative estimates of tax multipliers (Mertens and Ravn 2013), to the effects of fiscal adjustments (Yang, Fidrmuc and Ghosh, 2015), and estimating the effects of fiscal consolidations (Alesina et al. 2017).

A key extension of the use of the narrative approach was by Ramey (2011), who discussed the importance of timing and demonstrated how failing to account for the anticipation effect could lead to differences in empirical results. Ramey argued that government shocks predetermined in a quarter are likely anticipated quarters in advance, thus nullifying the notion that the shock is unanticipated. She created a narrative variable of estimates of changes in government spending shocks from news reports to capture the "news" component of government spending shocks. Our paper contributes to this strand of literature and follows the narrative approach through the use of a daily database of fiscal policy measures where measures are identified both at the date of their announcement and implementation.

A second strand of the literature our paper contributes to uses high-frequency data to assess the impact of monetary and fiscal policy. On the monetary policy front, Gurkaynak, Sack and Swanson (2004) were of the first to investigate the effects of US monetary policy on asset prices using high-frequency event studies. They find that monetary policy statements have a greater impact on asset prices than changes in the federal funds rate target. Gertler and Karadi (2015) show that shocks identified using high frequency surprises around policy announcements as external instruments generate responses in output and inflation which are similar to monetary VAR analyses. Auerbach and Gorodnichenko (2016) use daily data on U.S. spending news (announced and actual payments) to examine their effect on the US dollar. They find that while the dollar immediately appreciates following announcements about government spending, actual payments do not affect the exchange rate. David, Guajardo and Yepez (2019) examine the effects of fiscal consolidation announcements on sovereign spreads in emerging market economies using daily data on consolidation announcements. They find that sovereign spreads decline significantly following news that austerity measures have been approved by the legislature in countries with high spreads, due to increased confidence effects. Beetsma et al. (2015) examine the effects of fiscal consolidations on private sector confidence by constructing a monthly dataset of fiscal consolidation announcements and confidence indicators. They find that consumer and producer confidence decline around announcements of consolidation measures. This paper adds to this strand of the literature by examining the effects of daily fiscal policy announcements on high-frequency economic activity indicators, including industrial production indices, manufacturing PMIs, unemployment rates, leading composite indicators, and sovereign CDS spreads.

As for the literature on the role of fiscal policy during the COVID-19 pandemic, Bennelech and Tzur-Ilan (2020) find that a country's credit rating is the most important determinant of its fiscal spending during the pandemic, resulting in lower income countries not being able to deploy fiscal policy tools effectively during the crisis. Gourinchas et al. (2021) study the effects of fiscal policy during the COVID-19 pandemic at the firm, sector, country and global level. They find that at the firm level a lack of government support increased SME failure rates, and that fiscal policy was in general poorly targeted, reaching firms which did not need it. At the global level, fiscal policy helped offset about 8% of the economic downturn, and reduced the share of demand-constrained sectors, leading to a preservation of employment in these sectors.

As for research which explores fiscal multipliers across time and countries, Ramey and Zubairy (2014) extend their narrative variable using Jordà's (2005) local projection method to examine the state dependence of fiscal multipliers. They find no evidence that multipliers differ according to the amount of slack in the economy, nor that government spending multipliers are higher when monetary policy is near the zero-lower bound. Nickel and Tudyka (2014) find that fiscal policy has larger multipliers for countries with lower public debt-to-GDP ratios. Iltzetki et al. (2013) find that the output effect of an increase in government consumption is larger in advanced economies, economies operating under a predetermined exchange rate, and those with low debt-to-GDP levels. This paper contributes to this strand of the literature by being the first to empirically examine the effects of fiscal policy announcements on economic activity during COVID-19 in a large set of countries, and how these effects vary across countries and the severity of the pandemic. The granularity of our database also provides a first assessment of the effectiveness of various types of policy measures.

III. Data

We assemble a comprehensive database of announced and implemented fiscal stimulus measures, economic activity indicators, financial variables, and COVID-19 infections, and containment measures on a daily basis. The daily database is complemented with monthly indicators of economic activity and confidence: industrial production indices, manufacturing PMIs, confidence CLIs, unemployment rates, and sovereign CDS spreads. In this section, we describe the collection of the fiscal measures and the construction of fiscal shocks used in the empirical analysis, while information on the other variables is provided in the Data Annex.

The main source of our data is *Yale's COVID-19 Financial Response Tracker* (CFRT), which documents key intervention measures in response to the COVID-19 pandemic by fiscal authorities, central banks, and other organizations throughout the world.[3] The database provides a breakdown of intervention measures by: i) proposal date (henceforth referred to as announcement date); ii) implementation date; iii) institutional authority under which measures are announced; iv) policy

[3] https://som.yale.edu/faculty-research-centers/centers-initiatives/program-on-financial-stability/covid-19-crisis

tools used; and v) magnitude of intervention method. We restrict the database to include only interventions which would be considered as fiscal support measures. The information from the Yale database is supplemented by, and cross-checked with, announcements provided by the *IMF Policy Tracker*, the *OECD Country Policy Tracker* and newspaper reports. In several instances, the numbers quoted by the dataset do not match what is reported by the IMF policy tracker and other sources. On such occasions, we extensively research the policy announcements through newspaper reports and announcement links in order to report our best assessment of the date, size, and type of announced measure. In addition, and in an effort to avoid double-counting, we remove entries which appear to be duplicates, as well as any entry which is reported as financing or concessional lending by the IMF or World Bank. More detailed measures towards building our database are included in the data annex.

We extract and read the narrative of each policy record and we group the policy measures identified tools into eight sub-categories: i) asset guarantees; ii) asset purchases; iii) capital injections; iv) credit guarantees; v) grants; vi) loans; vii) payment forbearances; and viii) tax relief measures. Following the IMF's classification of fiscal measures, grants, payment forbearances (on tax payments and pension contributions) and tax relief interventions are recorded as *above-the-line measures*, as these measures are likely to be reflected in the fiscal balance and government debt.[4] All other interventions fall under the scope of *below-the-line measures*, i.e., measures which have no immediate or upfront effect on a government's deficit.

[4] https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19

We also classify each measure as *demand-support* and *emergency lifeline*.[5] Demand-support measures are identified as those which boost demand and household of firm disposable income, and typically include cash transfers, unemployment insurance, wage subsidies, reduction or deferral of social security or tax payments, paid sick leave, etc. In addition, public investments or healthcare spending measures are considered demand-support measures, given that their role does not entail providing cashflow support. Meanwhile, emergency lifeline measures are identified as those which provide sustained cashflow support to households and firms. Such measures include loans and umbrella guarantees to firms and households, government provision of loans, equity injections, and other liquidity support measures. From an accounting standpoint, most emergency lifelines form the bulk of below-the-line measures. Meanwhile, demand-support measures mainly fall under the above-the-line measures. Further details on the identification of measures is explained in the Data Annex.[6]

The dataset covers daily fiscal policy measures for 52 countries for which data on industrial production and PMI manufacturing is available, from January 1 to December 31, 2020. All data is converted to USD and then scaled to a percent of a country's 2019 GDP.

For the empirical analysis, we purge the daily announcements from lagged daily measures of activity that have been recently used to track the economic effects of the COVID-19 crisis such as Nitrogen Dioxide (NO_2) emissions (Lin and McElroy, 2011), international and domestic flights

[5] While some measures (such as cash transfers, unemployment benefits, paid sick leave) are typically identified as demand-support measures, they often provided emergency lifelines to households during the lockdown period, helping to reduce mobility by allowing workers to stay home and contain the pandemic.

[6] While the majority of the loans in the database provided were to SMEs and businesses, some examples of loans to households were in the form of loan forbearances on mortgages, student auto and credit card loans (which differ from payment forbearance on taxes or pension). In some countries, loans were extended to households through the creation of loan facilities - for instance the term Asset-Backed Securities Loan facility in the United States - through which the Federal reserve supported lending by lending to holders of asset backed securities collateralized by new loans. The issuance of asset-backed securities funded a wide range of lending, including student, auto and credit card loans.

(Deb, Furceri, Ostry, and Tawk, 2020), and mobility indicators (IMF 2020; Maloney and Taskin, 2020), and daily financial variables that can help capture expectations regarding future economic activity—such as bilateral exchange rate and stock market indices. Controlling for this information allows us to purge fiscal announcements of any predictable components. The residual of the regression is our shock. For robustness, several fiscal shocks are created, based on different combinations of high-frequency indicators. The results are available upon request.

IV. Stylized Facts on Fiscal Announcements

The database of announced and implemented fiscal stimulus measures confirms the unprecedented scale of the fiscal packages announced in response to the pandemic. Across the sample of 52 countries, comprising 27 advanced and 25 emerging market and developing economies, the largest announced intervention by an advanced economy was about 35 percent of 2019 GDP (Japan) while for an EMDE it was about 15 percent of GDP (Indonesia). This is in line with the overall trend where measures deployed by advanced economies were larger than those deployed by EMDEs—the mean fiscal stimulus response for advanced economies was about 12 percent of GDP, compared to a 4 percent average response in an EMDE (Figure 1).

Turning to the timing of the measures, Figure 2 reports the announced fiscal measures on a daily basis. It shows that responses were most frequent and significant in the months of March and April, which represent the acute first stage of the COVID-19 pandemic for most countries. Advanced economies responded faster, with 10 advanced economies announcing stimulus measures on March 16, 2020. They were quickly followed by emerging market economies in the ensuing days. Responses continued well into June 2020, but then diminished petered out, owing to dwindling fiscal space but also the relaxation of containment measures towards the end of 2020Q2 in many countries, that prompted the authorities to use more targeted measures.

Figure 3 reports the evolution of emergency lifelines and demand-support measures. The rollout of emergency lifelines was also concentrated during March and April 2020—the most stringent phase of the lockdown—but they continued to be of use throughout the year. And while lifelines were used together with demand support measures in the initial phase of the lockdown, the latter—which includes measures to boost households and firms' disposable income—seemed to pick up towards the end of the second quarter of 2020 (Figure 3), which coincides with the beginning of reopening in many countries.

Across policy tools, loans to households and businesses, as well as credit guarantees, made up the bulk of lifeline measures used during 2020. They were more frequently used in EMDEs. Grants (including cash transfers, wage subsidies, healthcare spending) and tax relief measures (tax cuts, tax payment deferrals) made up most of demand support measures (Figure 4). In terms of magnitude, the largest fiscal policy tools in the case of AEs were credit guarantees, grants (including cash transfers, wage subsidies, healthcare spending), tax relief measures (tax cuts, tax payment deferrals) and loans. For EMDEs, grants, payment forbearances and loans were the largest three types of instruments used (Figure 5).

Finally, about 70 percent of stimulus measures for both AEs and EMDEs were below-the-line measures, likely reflecting the importance of limited fiscal space in determining the size and nature of stimulus packages. Countries facing tighter constraints (measured by higher debt to GDP levels) relied more on below-the-line measures, while countries with relatively more space favored above the line measures (Figure 6).

V. Analysis

A. Effects of fiscal shocks at daily and weekly frequency

We follow Jordà (2005) to assess the dynamic effect of fiscal policy announcements at the daily frequency on bilateral exchange rates and stock prices, and at weekly frequencies on the OECD weekly tracker. The methodology (also used by Auerbach and Gorodnichenko (2013, 2016), Ramey and Zubairy (2018), and Alesina et al. (2019) among others) does not impose the dynamic restrictions embedded in vector autoregressions and is particularly suited to estimating nonlinearities in the dynamic response. The first regression we estimate is:

$$S_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} F_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta S_{i,t-\ell} + \varepsilon_{i,t+h} \quad (1)$$

where $S_{i,t+h}$ represents the logarithm of the daily (weekly) economic indicator (stock prices, bilateral exchange rates, the OECD economic activity tracker) in country i observed at date t; $F_{i,t}$ is the daily (weekly) fiscal announcements; u_i are country-fixed effects to account for time-invariant country-specific characteristics; X is a vector of control variables which includes lags of the containment measures, the amount of number of COVID-19 infections and deaths in country i observed at date t, and country time-trends.[7]

Equation (1) is estimated for each day h=0,..,30 (15 for weekly indicators). Impulse response functions are computed using the estimated coefficients θ_h, and the 90 and 95 percent confidence bands associated with the estimated impulse-response functions are obtained using the estimated standard errors of the coefficients θ_h. Equation (1) is estimated using Driscoll-Kraay (1998) standard errors to account for cross-sectional and time dependence

[7] In case we are estimating the effect of fiscal shocks on exchange rates (stock prices), we ensure that the fiscal shock is not already purged at the initial stage from the exchange rate (stock prices).

in the error term Figure 7 shows the estimated dynamic response of stock market prices and bilateral exchange rate to fiscal stimulus measures over the 30-day period following their announcement, together with the 90 and 95 percent confidence interval around the point estimate. The left-hand panel shows the cumulative response of bilateral exchange rates, while the right-hand panel shows the cumulative response of stock market prices.

Consistent with the literature on the effect of fiscal announcements at the daily level (Auerbach and Gorodnichenko 2016), the results provide evidence that fiscal stimulus announcements in 2020 led to an appreciation of bilateral exchange rates of about 5 percent 30 days after their announcement. Similarly, fiscal stimulus announcements led to stock market cumulative gains of 40 percent logs following their announcement. At the weekly frequency, the results in Figure 8 also highlight that announced fiscal measures significantly boosted economic activity as proxied by the OECD weekly tracker.

B. Effects of fiscal shocks at the monthly frequency

We then turn to standard indictors of economic activity such as industrial production, unemployment, etc. The advantage of using these indicators it that it allows to infer about the fiscal multiplier associated to these measures and relate our results to those presented in the previous literature. The main drawback is the limited time dimension of the sample (12 observations per country) which prevents us to look into dynamic effects.

To estimate the (unconditional) impact of fiscal shocks on monthly economic activity indicator, we use the following equation, for an unbalanced sample of 52 economies from January to December 2020:

$$\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $Y_{i,t}$ is the indicator of economic activity—as typically in the literature of the effectiveness of monetary policy, we use industrial production as preferred indictor, but we also consider alternative measures of economic activity such unemployment, manufacturing PMI, the OECD CLI and sovereign CDS spread—of country i in month t. $\Delta Y_{i,t}$ alternately denotes the growth rate of industrial production (year on year), the growth rate of the composite leading indicator (year-on-year), PMI at its level given that it is already a percent variable, the change in unemployment rate (defined as the difference between the current and previous month), and the level of CDS spreads. $Shock_{i,t}$ denotes the fiscal shock at the monthly frequency—following Gertler and Karadi (2015), we aggregate the daily shocks into monthly average shocks to study the effect of fiscal measures on a range of economic activity indicators. In the baseline, we use the simple average of all the daily measures. The results are similar and not statistically different when we use a weighted average of daily shocks, with higher weights for shocks occurring at the beginning of the month. u_i are country-fixed effects to account for time-invariant specific factors. $X_{i,t}$ is a vector of control variables including containment measures, retail, mobility the number of COVID-19 infections and fatalities, monetary policy announcements and policy rate changes; and $\varepsilon_{i,t}$ is the error term. Equation (2) is estimated using Driscoll-Kraay (1998) standard errors to account for cross-sectional and time dependence in the error term.

The results from the baseline monthly regressions are summarized in Table 1. They show that fiscal measures announced by countries during COVID-19 have been effective in boosting economic activity and confidence, as well as reducing unemployment and compressing CDS spreads. In particular, we find that a one percent of GDP fiscal shock has led, on average, to a 0.25 percent increase in the growth rate industrial production (year-on-year). To compare this result with the literature on fiscal multipliers, back of the envelope calculations based on the historical relationship between industrial production and GDP would imply a fiscal multiplier of about 0.2.[8]

Beyond industrial production, we find that fiscal measures had economically and statistically significant effects on other measures of economic activity such as manufacturing PMI (0.39 percent increase) and confidence indicators such as OECDs composite leading indicator (about 0.1 percent). The effect is also significant on unemployment and sovereign CDS spreads, with a one percent of GDP fiscal shock leading to a decline in the monthly unemployment rate by 0.06 percentage point, and a narrowing of sovereign CDS spreads by about 0.05 bps. The reduction in the CDS spreads following the announcement of fiscal measures suggests that the measures were seen by the markets as positive news for debt sustainability. However, and in line with the findings of Beetsma et al. (2015) on the role of institutional quality in shaping the response of confidence indicators to fiscal consolidation, we find that the reduction in CDS spread is statistically significant only for advanced economies, where fiscal credibility is more established.[9]

We perform several robustness checks of our results. To further address endogeneity concerns related to the possibility that fiscal announcements are correlated with other factors and policy measures (such as monetary policy actions) affecting economic activity, we extend the set of controls to include monetary policy announcements and policy rate changes, COVID-19 fatalities and retail mobility, and expectations of economic activity based on monthly consensus

[8] Historically, a one percentage point change in GDP growth results in a 0.9 percent increase in industrial production (Table A11), based on the reduced equation $\frac{\Delta IP}{IP} = K * \Delta Y/Y$, with $K = 0.9$. Our regressions estimating the effect of the fiscal shock on industrial production is based on reduced equation $\frac{\Delta IP}{IP} = \beta * \Delta G/Y$, where β = 0.25. Therefore, the multiplier effect is translated to GDP with the following $\frac{\Delta Y}{\Delta G} = \frac{\beta}{k}$, and is equal to 0.2.

[9] The results are available upon request.

GDP growth forecasts. These results are reported in Table 2 (for industrial production) and Annex Tables A1-4 (for other economic indicators) and are robust to these controls. We also replicated the results with the extended set of controls to include time fixed effects (Table 3, as well Annex Tables A1-4). As a further step, we also include the lagged dependent variable in each of our regressions (Table 4) to explicitly control for the time-dependence in the monthly shocks.

In the baseline we aggregated daily fiscal shocks into monthly using simple average. To check the robustness of our results, we compute the fiscal shocks based on alternative weighting schemes. In particular, instead of computing shocks as a monthly average of the daily shocks (equal weights to all days of the month), we assign higher weights to announcements in earlier weeks of the month, with the rationale that shocks which take place earlier in the month may have larger effect, as there is more time for their impact to materialize on monthly economic indicators. Specifically, we create a fiscal shock where 45 percent of its weight is assigned for the announcements made in the first ten days of the month, followed by 35 percent of the weight being assigned for announcements the next 10 days, and 20 percent for the remainder of the days of the month. The results obtained with this alternative weighing scheme are presented in Table 5 and are similar to, and not statistically, different from the baseline.[10]

The results presented so far are based on announcements as forward-looking agents are expected to respond to announcements rather than fiscal actions (Ramey 2011; Auerbach and Gorodnichenko, 2013). In the case of the COVID-19 crisis, however, fiscal measures were rolled out quite quickly, with many of implemented only few days they were announced.[11] But given the

[10] We experiment with different weightings (giving higher weights for the first week, first 10 days, etc.) and obtain similar results. Similar findings are also obtained for other economic indicators and are available upon request.

[11] In our database, for most, there is only about a 1-week delay between the announcement and implementation.

presence of some announcements with longer lags for a few countries, and in order to test the robustness of our results, we repeated the analysis constructing fiscal shocks based on implementations dates. The results reported in Table 6 show are broadly similar to those obtained with announcements.[12]

C. Country Characteristics

We analyze whether the impact of fiscal shocks vary depending on country-specific conditions, such as countries' s structural characteristics (e.g., the level of development, trade openness, the level of public debt before the crisis) and the severity of the pandemic and lockdown restrictions. For this purpose, we extend Equation (2) as follows:

$$\Delta Y_{i,t} = \alpha + u_i + F(z_{it})\beta_L Shock_{i,t} + \left(1 - F(z_{it})\right)\beta_H Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t} \quad (3)$$

$$\text{with } F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1 - exp^{-\gamma z_{it}})}, \quad \gamma = 1.5 \quad (4)$$

where z is a country-specific characteristic normalized to have zero mean and a unit variance. The approach allows us to exploit cross-country variation by looking at country-specific characteristics (such as debt levels), as well as within-country variation, by examining how fiscal shocks differ depending on a country's containment level for instance. The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(z_{it})$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. For instance, $F(z_{it})$= 1 would correspond to a country with very high social mobility, while $F(z_{it})$= 0 would correspond to a country with very low social

[12] Results for other variables using implementation dates are also robust with additional controls and are available upon request.

mobility. This approach is equivalent to the smooth transition model developed by Granger and Teravistra (1993).

Our results on how country characteristics affect the impact of fiscal shocks are summarized in Table 7. Consistent with most of the evidence in the literature, we find that fiscal shocks have been more effective in advanced economies (Ilzetki et al., 2011). Second, we find that fiscal shocks are likely to be much more effective in countries with lower public debt levels before the crisis, as the crowding out effects on private investment and consumption are typically larger in countries with high debt (Nickel and Tudyka 2014; Furceri and Zdzienicka, 2020). The results are confirmed for other economic indicators. In particular, and consistent with the view that fiscal actions were seen by the market as important stabilization tools, we see stronger and statistically significant decline in CDS spreads for countries with lower public debt.[13]

In contrast, and somewhat unsurprisingly, we do not find evidence that effects vary with the degree of trade openness. This is likely due to the limited cross-country variation in our sample since most of the countries are relatively open and with flexible exchange rates, and the fact that trade was generally anemic during the crisis.

D. Type of Fiscal Measures and the Pandemic Cycle

Finally, we extend the baseline specification to test whether the impact of fiscal measures varies by type of measure deployed. In particular, we extend Equation (2) as follows:

$$\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t} \quad (5)$$

[13] Results (not reported) show a narrowing of 0.15 bps of sovereign CDS spreads following a fiscal shock in countries with lower public debt-to-GDP ratio, in comparison to a 0.04 bps narrowing in countries with higher debt ratios. Note that in the stylized facts, we show that countries with lower public debt have relied more on above-the-line measure. Given that above-the-line measures have been, on average, less effective in stimulating economic activity, the results of higher effects for lower debt countries do not seem to be driven by different compositions of the fiscal measures.

$$\Delta Y_{i,t} = \alpha + u_i + \beta BL_{i,t} + \gamma AL_{i,t} + \theta X_{i,t} + \varepsilon_{i,t} \quad (6)$$

where $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. We follow Alesina, Favaro and Giavazzi (2014) who study the effects of tax-driven or expenditure-based austerity by distinguishing whether fiscal plans are expenditure based or taxed based depending on whether the largest component of a fiscal correction was an increase in taxes, or a decrease in expenditure.[14] In that context, we set the emergency lifeline (demand-support) dummy as equal to 1 (zero) for any given country if emergency lifelines (demand-support measures) make up more than 50 percent of its entire fiscal stimulus package in 2020. Similarly, $BL_{i,t}$ is a below-the-line dummy interacted by the fiscal shock to represent a below-the-line package, while $AL_{i,t}$ is an above-the-line dummy interacted by the fiscal shock to represent a fiscal package of above-the-line measures.

While on average, fiscal measures seemed effective in boosting economic activity and confidence, their effectiveness may differ depending on the type of measure—above-the-line, below-the-line, emergency lifeline, or demand support measure—that was used. For example, it is reasonable to assume that demand support measures (the bulk of which are classified as above-the-line measures) are likely to be less effective during lockdowns when supply constraints are binding. In contrast, emergency lifelines that are aimed to reduce supply constraints, keep firms operating and workers employed are likely to be more effective during lockdowns.

[14] As noted in Alesina, Favaro and Giavazzi (2014), this approach saves degrees of freedom by first studying the correlation between unanticipated and anticipated total adjustments and then by distinguishing between tax-based and expenditure-based adjustments.

The results summarized in Table 8 seems confirm this intuition, with emergency lifelines having a larger impact out than demand-support measures during our COVID-19 sample, on average. Similar results are obtained when we look at below- and above-the-line measures. The reason is that a big bulk of lifelines measures—which include loans, credit guarantees, provisions provided to firms, etc.—have been typically categorized as below-the-line measure (indeed the correlation between below-the-line measures and emergency lifelines is around 0.8).

Similar results hold for other economic indicators (Annex Tables A5-8) and when choosing different thresholds to differentiate between emergency lifelines and demand-support measures (see Annex Table A9 for 60 percent as a threshold).[15]

These results, however, mask important heterogeneity with respect to the pandemic cycle. In particular, we find that emergency lifelines were more effective when containment measures were high, as they provided much needed cashflow and liquidity support during the constrained months of economic activity (Table 9). This supports our earlier result that lifeline policies have been more effective on average, since the bulk of the fiscal policy announcement came during times of strict lockdown. In contrast, our results show that the effect of demand-support measures are much stronger when containment measures are being eased, which allows for more opportunities of increased domestic consumption. Similar results are obtained when we look at mobility—lifelines are more effective when mobility is low, while and the coefficient for demand-support is high with high mobility, though the result is not statistically significant (Table 10). The results reported in Table A10 are also robust to alternative thresholds.

[15] Results are also robust to different thresholds (65, or 70 percent) and are available upon request.

Again, we get similar results when differentiating between above- and below-the-line measures given the high correlation between above-the-line and demand-support measures, and below-the-line and lifelines.

VI. Conclusions

Countries worldwide launched historically unprecedented fiscal support measures to offset the economic fallout of the COVID-19 pandemic. To quantify the economic effects of these measures, we assemble a novel daily database of announcements regarding the fiscal policy interventions implemented across 52 countries throughout 2020—the use of daily frequency is key to reduce the risks that announcements react to developments in the economy.

The results demonstrate that announced fiscal policy measures in response to the COVID-19 pandemic have, on average, been effective in stimulating economic activity, as captured by a range of high-frequency indicators, namely industrial production, manufacturing PMI, unemployment, confidence indicators, and sovereign CDS spreads. The effects are economically and statistically significant and robust to alternative econometric specifications. In addition, emergency lifelines measures such as loans to firms and households, umbrella guarantees and equity injections (which form the bulk of below-the-line measures) were more effective in boosting economic activity during period of lockdown and supply side shocks, while demand-support measures—including tax cuts or payment deferrals, cash transfers and unemployment insurance—were less significant, on average.

Country characteristics play an important role in the effectiveness of fiscal policy, with larger effects for advanced economies and countries with lower public debt levels. In addition, a country's stage in the pandemic cycle is critical, with emergency lifelines more effective when containment measures are high and supply is constrained, while demand-support measures are more effective when containment measures are being eased, and domestic consumption opportunities are more plentiful.

Our findings highlight the important role played by fiscal policy during the COVID-19 crisis. By supplementing the literature with quantitative empirical estimates, our paper can help policy makers make informed decisions on fiscal spending during the pandemic. One primary policy lesson derived from this analytical exercise is that emergency lifelines should not be withdrawn prematurely as they have been vital to support the economy during the COVID-19 crisis. But as supply constraints from containment measures abate, demand-support policies—including through investment in digital and green infrastructure—will be more effective and can replace emergency lifelines. In countries with high debt, fiscal policy is less effective and monetary policy might have to play a larger role to support economic activity.

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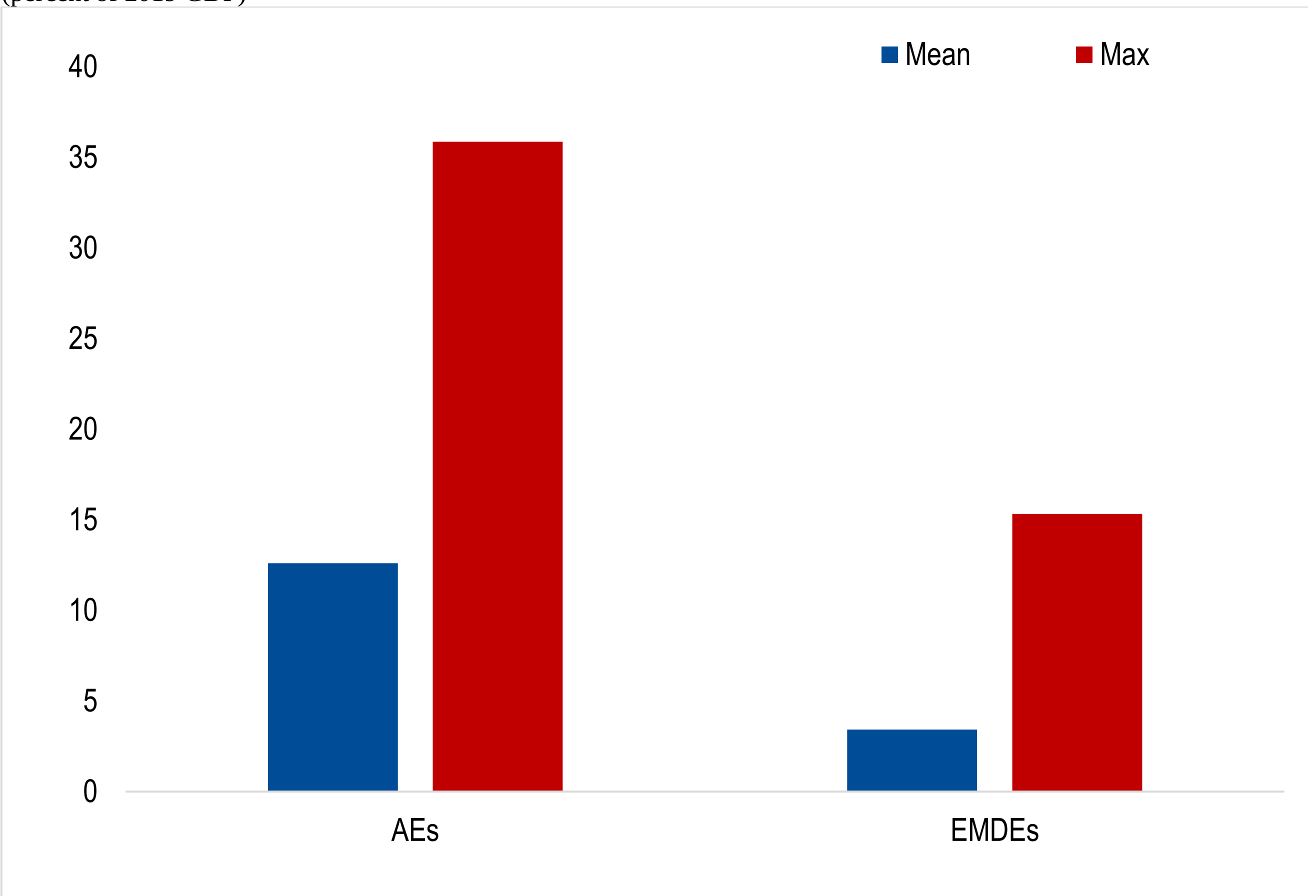
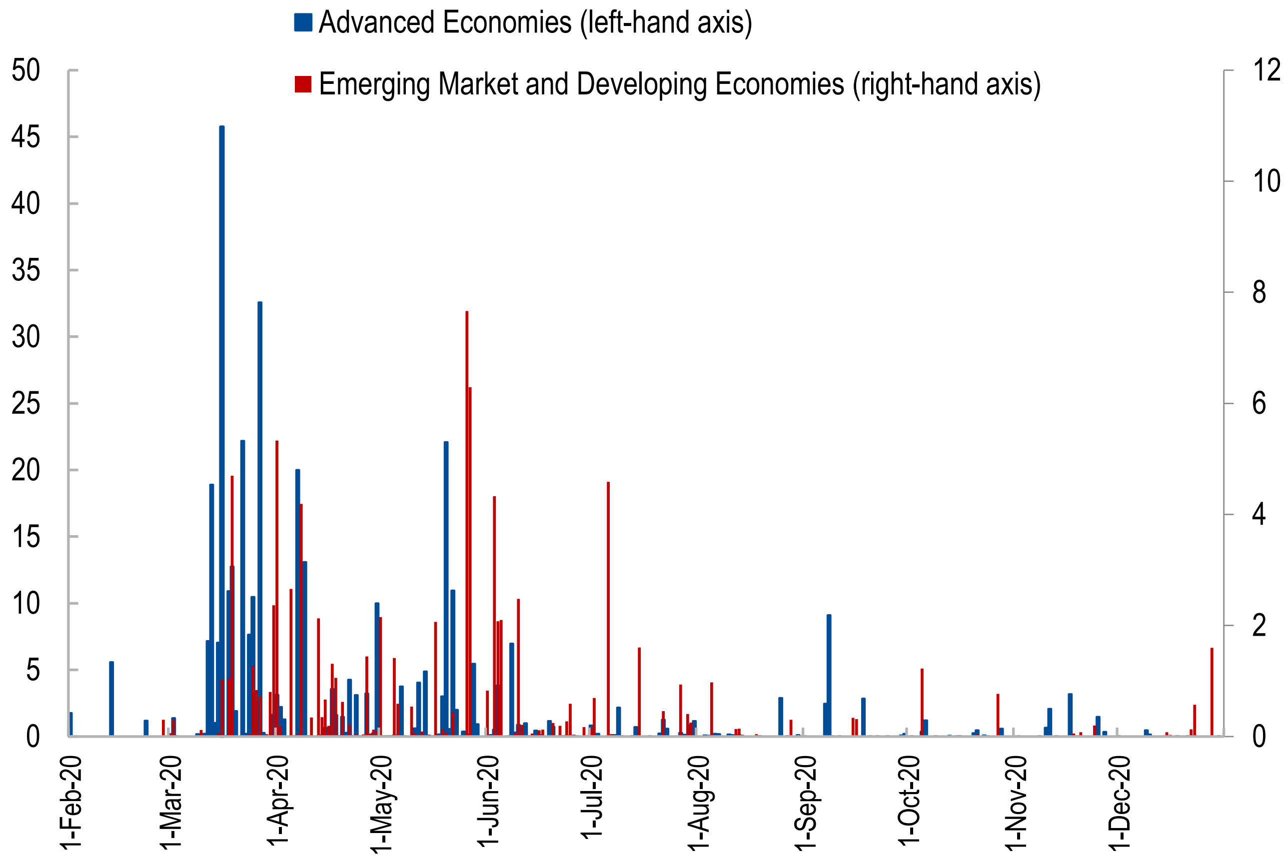
Figures

Figure 1. Fiscal Stimulus Packages by Magnitude
(percent of 2019 GDP)



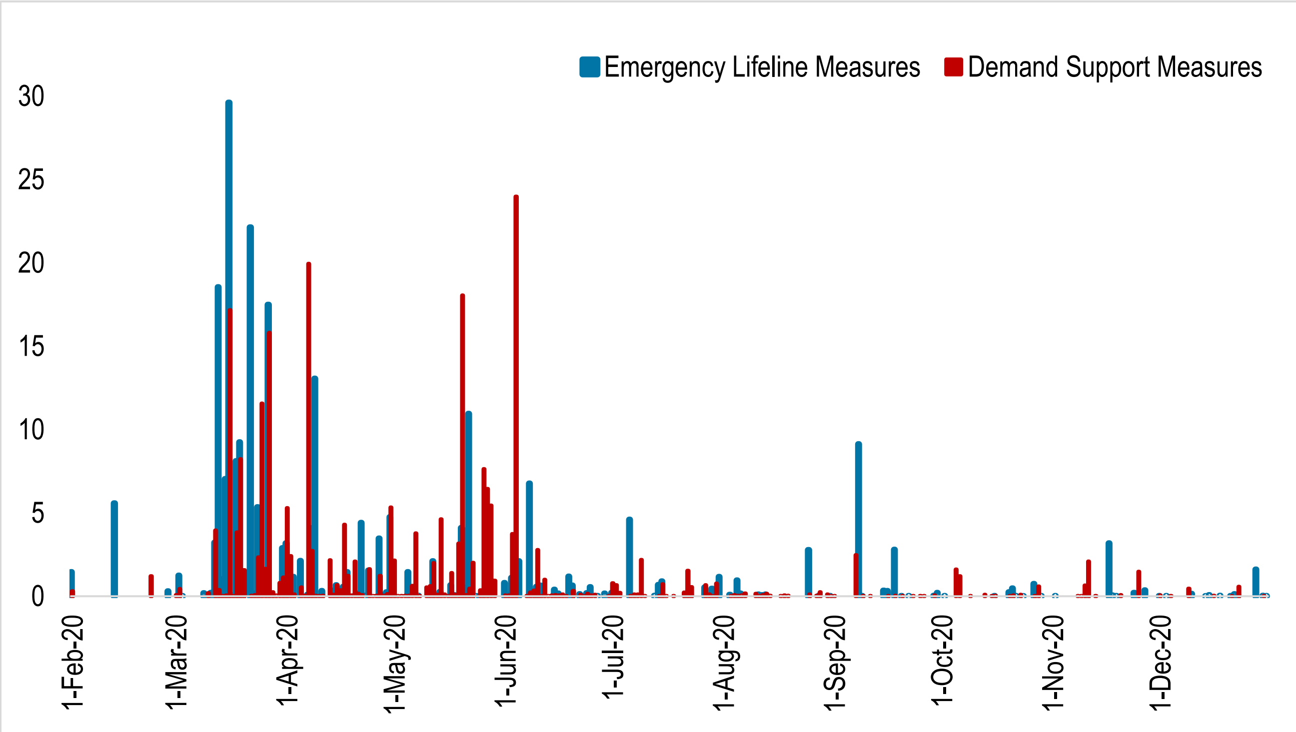
Note: the figure above reports mean and maximum fiscal package size across 52 countries (27 advanced economies and 27 emerging market and developing economies) scaled as a percent of their respective 2019 GDP over the year 2020.

Figure 2. Fiscal Stimulus Measures During the COVID-19 Pandemic (percent of 2019 GDP)



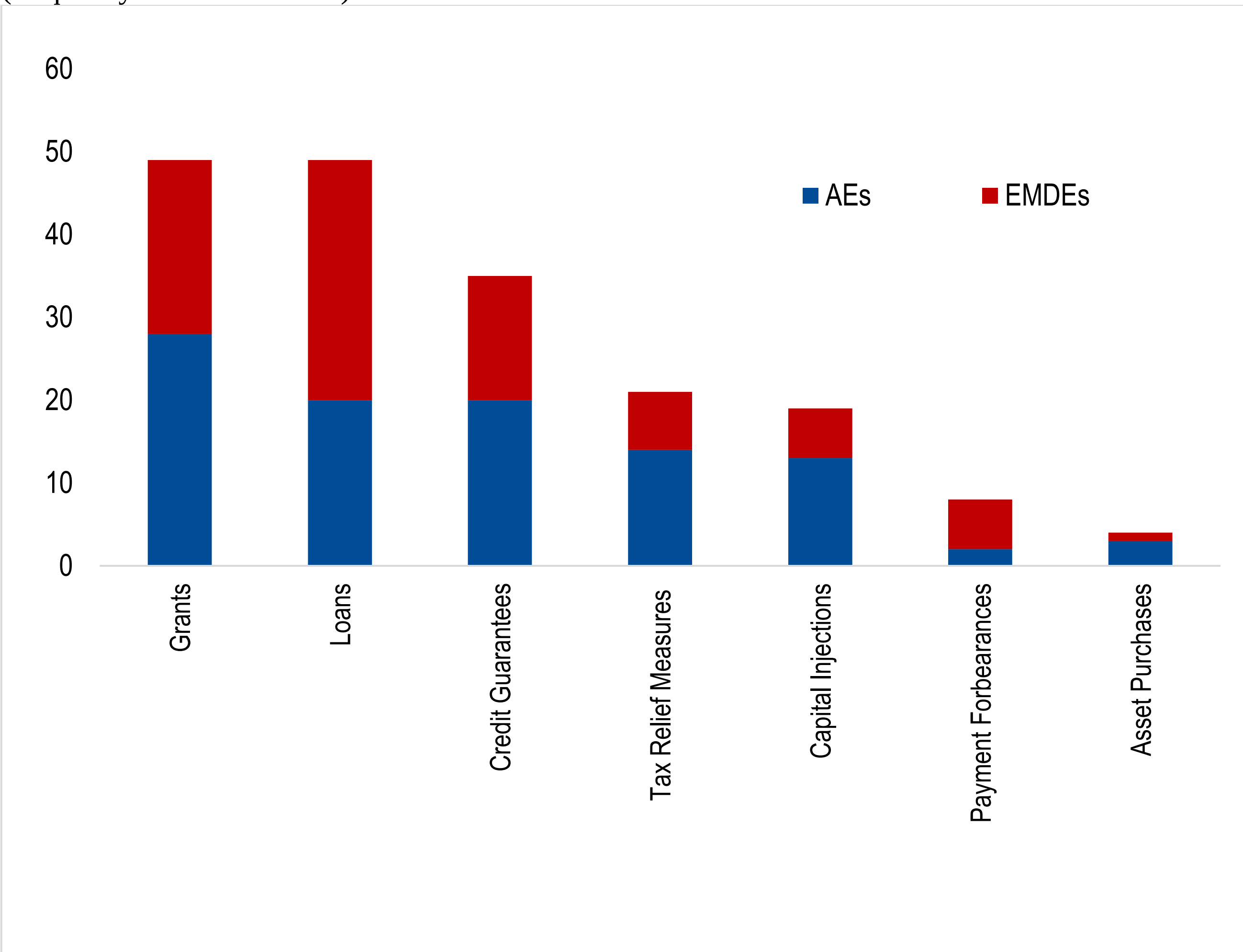
Note: the figure above reports daily announced fiscal stimulus measures of 52 countries (27 advanced economies and 27 emerging market and developing economies) scaled as a percent of their respective 2019 GDP over the year 2020.

Figure 3. Fiscal Stimulus Measures by Type During the COVID-19 Pandemic (percent of 2019 GDP)



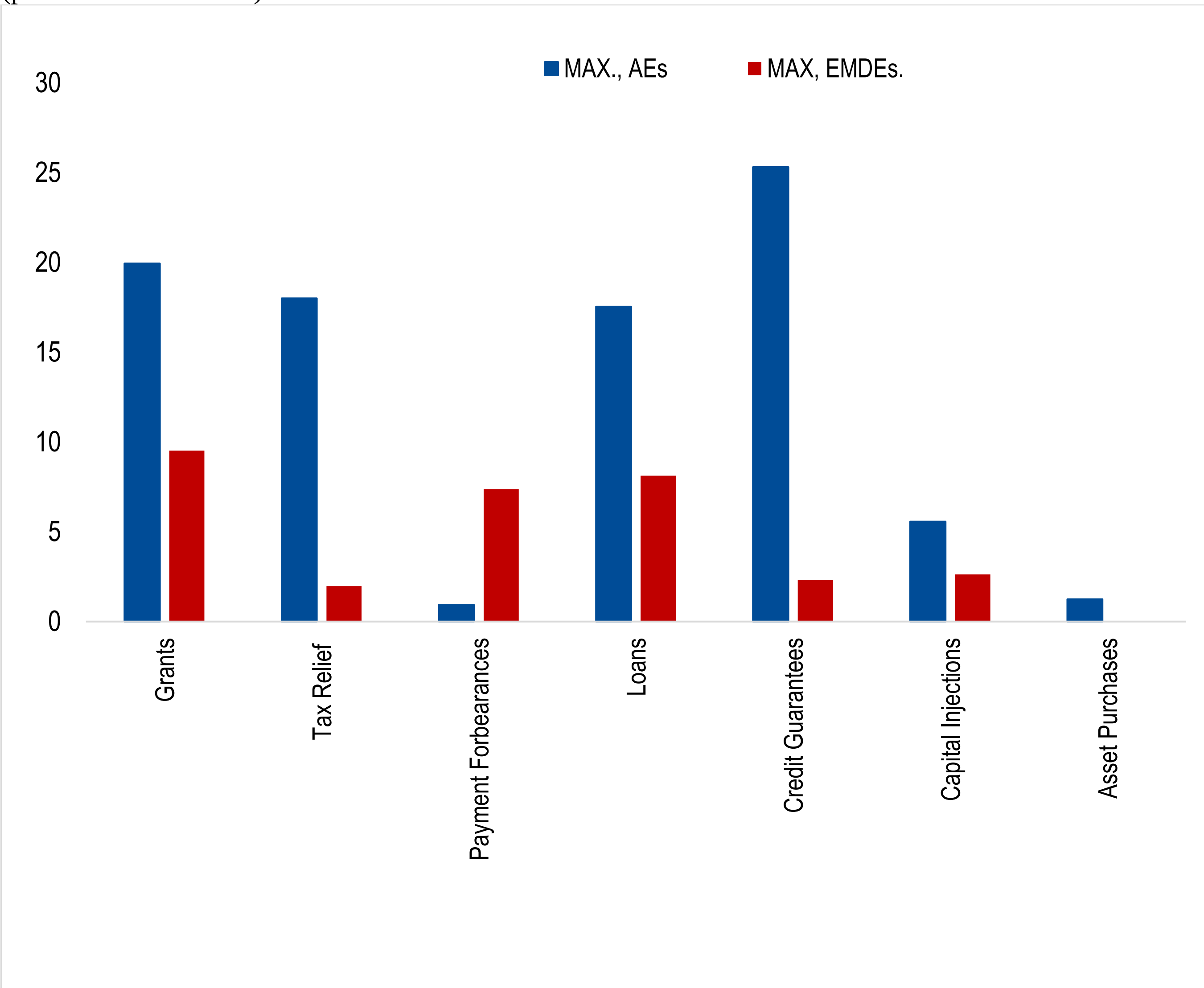
Note: the figure above reports daily announced emergency lifeline and demand support measures of 52 countries (27 advanced economies and 25 emerging market and developing economies) scaled as a percent of their respective 2019 GDP over the year 2020.

Figure 4. Fiscal Measures, by Policy Tool
(frequency of measure used)



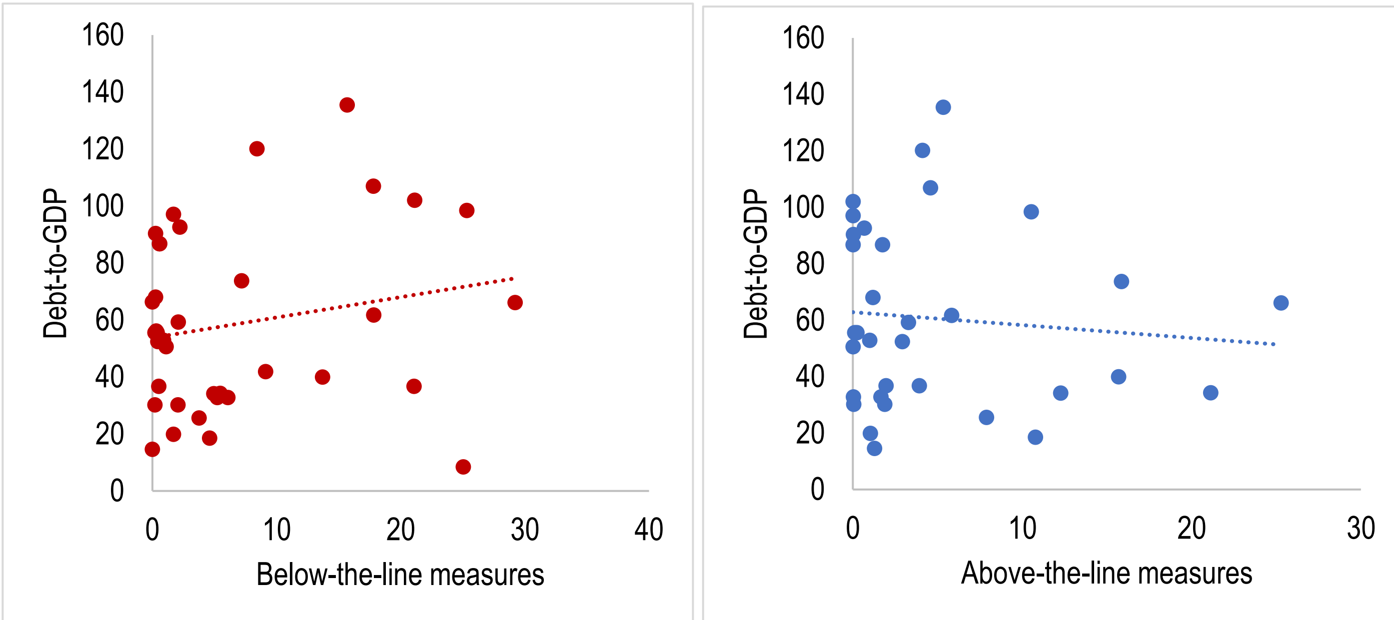
Note: the figure above reports the frequency of fiscal policy tools used during 2020 by 27 AEs and 25 EMDEs.

Figure 5. Fiscal Measures, by Type and Magnitude
(percent of 2019 GDP)



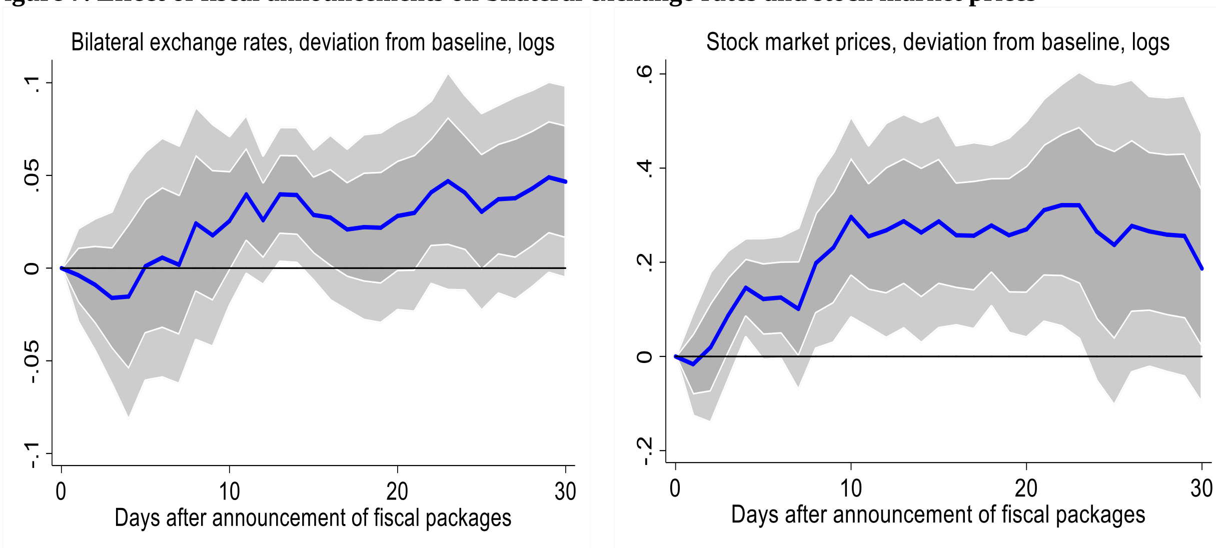
Note: the figure above reports maximum fiscal policy tool size used during 2020 by 27 AEs and 25 EMDEs, scaled as a percent of their respective 2019 GDP over the year 2020.

Figure 6. Fiscal Measures by Type and Fiscal Space Considerations



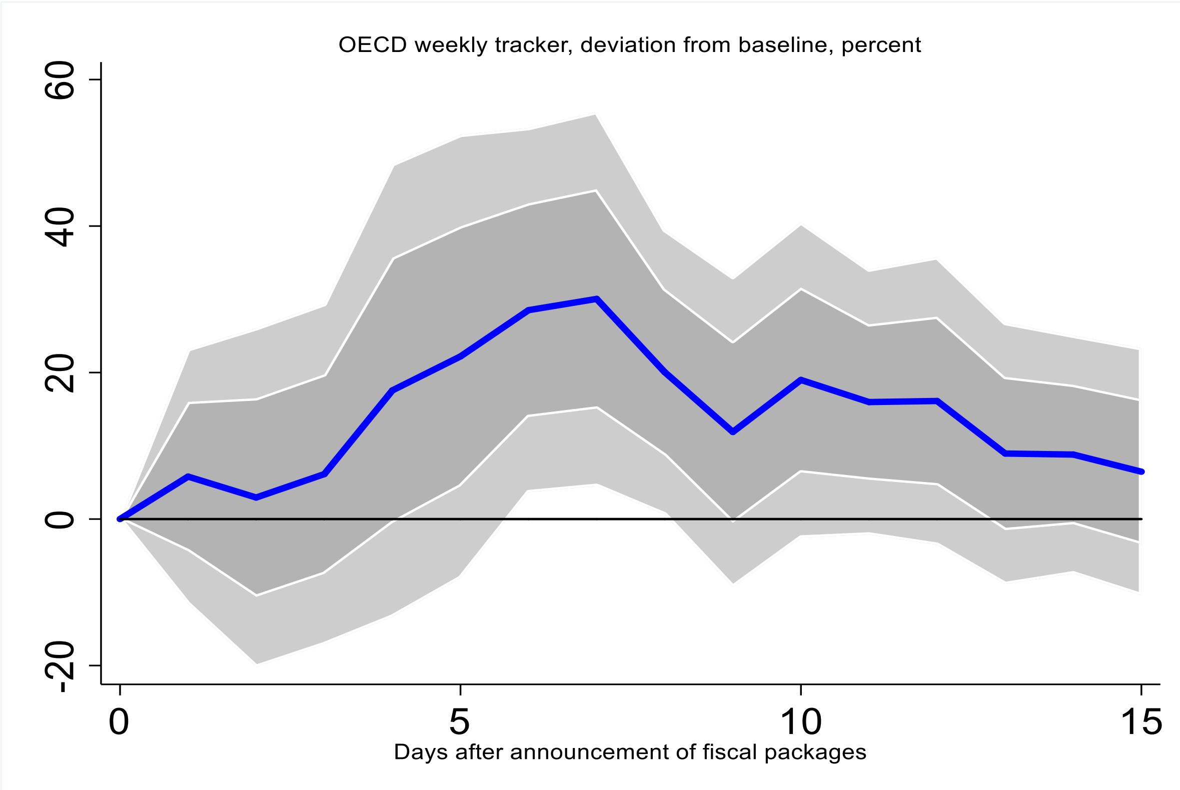
Note: The charts depict the relationship between above-the-line and below-the-line measures announced, and debt-to-GDP levels. Fiscal measures and debt-to-GDP are reported as a percent of each country's 2019 GDP.

Figure 7. Effect of fiscal announcements on bilateral exchange rates and stock market prices



Note. Impulse response functions are estimated for a sample of 42 countries using daily data from January 1, 2020 to December 31, 2020. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the announcement of fiscal stimulus measures. Estimates based on $S_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} F_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta S_{i,t-\ell} + \varepsilon_{i,t+h}$ where $S_{i,t}$ is the logarithm of the bilateral exchange rate or stock market prices in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $F_{i,t}$ denotes the announced fiscal measures as a share of GDP; X is a matrix of time varying control variables and country specific time trends. (For the bilateral exchange rate, increase denotes appreciation).

Figure 8. Effect of fiscal announcements on the OECD weekly tracker



Note. Impulse response functions are estimated for a sample of 46 countries using weekly data from January 1, 2020 to December 31, 2020. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the announcement of fiscal stimulus measures. Estimates based on $S_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} F_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta S_{i,t-\ell} + \varepsilon_{i,t+h}$ where $S_{i,t}$ is the weekly economic tracker (in percent) in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $F_{i,t}$ denotes the announced fiscal measures as a share of GDP; X is a matrix of time varying control variables and country specific time trends.

Tables

Table 1. Baseline effect of announced fiscal measures on economic activity

	(1)	(2)	(3)	(4)	(5)
	Industrial Production (y-o-y growth)	PMI Manufacturing	Composite Leading Indicator (y-o-y growth)	Unemployment Rate (change)	CDS Spreads
Fiscal Shock	0.254***	0.190**	0.089*	-0.053**	-0.0443***
	(0.057)	(0.074)	(0.043)	(0.017)	(0.008)
Containment Measures Index	-21.212***	-19.780***	-8.538***	-0.685	10.261***
	(3.497)	(2.388)	(1.479)	(0.592)	(3.293)
COVID-19 Cases	-0.928***	-0.050	-0.185**	0.073	-0.586*
	(0.194)	(0.197)	(0.067)	(0.094)	(0.294)
Constant	Yes	Yes	Yes	Yes	Yes
Observations	480	382	396	292	600
R-squared	0.565	0.648	0.602	0.0219	0.388
Number of countries	40	32	33	30	50

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country i at month t; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 2. Robustness check: additional controls

	(1)	(2)	(3)	(4)	(5)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
Fiscal Shock	0.285***	0.251***	0.301***	0.333***	0.317***
	(0.068)	(0.055)	(0.059)	(0.075)	(0.068)
Containment Measures Index	-11.296*	-21.929***	-21.540***	-8.877***	-10.698***
	(6.055)	(3.468)	(6.292)	(1.078)	(1.148)
COVID-19 Cases	-2.683***	-0.892***	-1.074***	-1.471***	-1.375***
	(0.349)	(0.187)	(0.231)	(0.162)	(0.150)
Consensus Forecasts (lagged)	-0.936***				
	(0.272)				
Policy Rate Change		-0.978***			-0.629**
		(0.289)			(0.230)
Monetary Policy Announcements		0.178***			0.146***
		(0.040)			(0.016)
New COVID-19 Fatalities			-0.402		0.755
			(0.647)		(0.699)
Retail Mobility				0.130***	0.154**
				(0.034)	(0.058)
Constant	Yes	Yes	Yes	Yes	Yes
Observations	220	444	440	428	395
R-squared	0.660	0.557	0.634	0.655	0.654
Number of countries	40	37	40	39	36

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country i at month t; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 3. Robustness check: with time fixed effects

	(1)	(2)	(3)	(4)	(5)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
Fiscal Shock	0.129*	0.139*	0.164**	0.179*	0.188**
	(0.066)	(0.063)	(0.069)	(0.085)	(0.083)
Containment Measures Index	-10.343**	-10.555**	-9.047**	0.424	0.244
	(3.915)	(4.030)	(2.986)	(3.058)	(3.354)
COVID-19 Cases	-0.230	-0.263	-0.022	1.086***	1.254***
	(0.165)	(0.165)	(0.254)	(0.113)	(0.136)
Policy Rate Change		-0.791***			-0.484**
		(0.194)			(0.195)
Monetary Policy Announcements		0.008			-0.024
		(0.039)			(0.034)
New COVID-19 Fatalities			-0.692*		0.002
			(0.326)		(0.186)
Retail Mobility				0.155**	0.162**
				(0.062)	(0.069)
Time FE	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Observations	480	444	440	428	395
R-squared	0.565	0.557	0.634	0.655	0.654
Number of countries	40	37	40	39	36

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 4. Robustness check: with lagged dependent variable

	(1)	(2)	(3)	(4)	(5)
	Industrial Production (y-o-y growth)	PMI Manufacturing	Composite Leading Indicator (y-o-y growth)	Unemployment Rate (change)	CDS Spreads
Fiscal Shock	0.240***	0.208**	0.079**	0.007	-0.024**
	(0.065)	(0.067)	(0.034)	(0.022)	(0.008)
Lagged Dep. Variable	0.173**	0.142*	0.251***	-0.684***	0.188
	(0.063)	(0.072)	(0.040)	(0.085)	(0.160)
Containment Measures Index	-24.519***	-21.261***	-8.927***	0.695	6.246**
	(5.084)	(3.091)	(1.767)	(0.624)	(2.180)
COVID-19 Cases	-0.517*	0.262	0.033	-0.260**	-0.330*
	(0.271)	(0.264)	(0.053)	(0.087)	(0.175)
Constant	Yes	Yes	Yes	Yes	Yes
Observations	440	352	363	251	550
R-squared	0.652	0.666	0.659	0.500	0.569
Number of countries	40	32	33	30	50

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 5. Robustness check: Alternative weights

	(1)	(2)	(3)	(4)	(5)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
Fiscal Shock	0.223***	0.216***	0.267***	0.286***	0.286***
	(0.062)	(0.062)	(0.059)	(0.068)	(0.068)
Containment Measures Index	-21.137***	-21.823***	-21.606***	-8.936***	-10.794***
	(3.533)	(3.509)		(1.159)	(1.265)
COVID-19 Cases	-0.931***	-0.897***	-1.073***	-1.471***	-1.375***
	(0.195)	(0.189)	(0.236)	(0.167)	(0.155)
Policy Rate Change		-0.986***			-0.635**
		(0.290)			(0.230)
Monetary Policy Announcements		0.175***			0.143***
		(0.040)			(0.016)
New COVID-19 Deaths			-0.367		0.793
			(0.652)		(0.707)
Retail Mobility				0.128***	0.154**
				(0.033)	(0.058)
Constant	Yes	Yes	Yes	Yes	Yes
Number of obs.	480	444	440	428	395
R-squared	0.564	0.552	0.633	0.655	0.651
Number of countries	40	37	40	39	36

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Fiscal shocks are aggregated from a daily to monthly frequency by assigning higher weights to the earlier weeks of the month (as opposed to a simple monthly average). Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 6. Baseline effect of implemented fiscal measures on economic activity

	(1)	(2)	(3)	(4)	(5)
	Industrial Production (y-o-y growth)	PMI Manufacturing	Composite Leading Indicator (y-o-y growth)	Unemployment Rate (change)	CDS Spreads
Fiscal Shock	0.269***	0.419**	0.094**	-0.104***	-1.006**
	(0.053)	(0.147)	(0.041)	(0.019)	(0.347)
Containment Measures Index	-21.180***	-45.138***	-8.515***	-0.661	10.248**
	(3.504)	(4.917)	(1.472)	(0.592)	(3.306)
COVID-19 Cases	-0.927***	0.495	-0.186**	0.065	-0.586*
	(0.192)	(0.413)	(0.067)	(0.093)	(0.296)
Constant	Yes	Yes	Yes	Yes	Yes
Observations	480	382	396	292	600
R-squared	0.565	0.653	0.602	0.0250	0.388
Number of countries	40	32	33	30	50

Note: results reported are based on a sample of 52 countries using daily data on implemented fiscal measures from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 7. Effect of announced fiscal shocks, by country characteristics

	(1)	(2)	(3)
	AEs vs EMDEs Industrial Production (y-o-y growth)	**Public Debt to GDP** Industrial Production (y-o-y growth)	**Trade Openness** Industrial Production (y-o-y growth)
High State * Fiscal Shock	0.264***	0.023	0.365
	(0.056)	(0.099)	(0.301)
Low State * Fiscal Shock	0.166	0.777***	0.148
	(0.394)	(0.132)	(0.203)
Containment Measures Index	-21.641***	-21.189***	-20.725***
	(3.500)	(3.196)	(3.418)
COVID-19 Cases	-1.011***	-0.918***	-0.918***
	(0.194)	(0.176)	(0.189)
Constant	Yes	Yes	Yes
F-test Difference	0.07	13.89*	0.2
Observations	468	456	444
R-squared	0.584	0.555	0.549
Number of countries	39	38	37

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + F(z_{it})\beta_L Shock_{i,t} + (1 - F(z_{it}))\beta_H Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}$, y = 1.5 . z is a country-specific characteristic 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 $F(z_{it})$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country i at month t; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 8. Effect of announced fiscal shocks on industrial production, by type of measure

	(1)	(2)	(3)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
Fiscal Shock	0.254***		
	(0.057)		
Fiscal Shock * Emergency Lifelines Dummy		0.414**	
		(0.140)	
Fiscal Shock * Demand Support Dummy		-0.049	
		(0.097)	
Fiscal Shock * Below-the-Line Measures Dummy			0.420**
			(0.137)
Fiscal Shock * Above-the-Line Measures Dummy			-0.074
			(0.090)
Containment Measures Index	-21.212***	-21.312***	-21.281***
	(3.497)	(3.579)	(3.549)
COVID-19 Cases	-0.928***	-0.911***	-0.913***
	(0.194)	(0.194)	(0.193)
Constant	Yes	Yes	Yes
Observations	480	480	480
R-squared	0.565	0.566	0.567
Number of countries	40	40	40
Share of emergency lifeline (below-the-line) measures		65%	68%
F-test difference		4.89	6.03*

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$ Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. The emergency lifeline (demand-support) dummy is equal to 1 (zero) for any given country in case emergency lifelines (demand-support measures) make up more than 50 percent of its entire fiscal stimulus package in 2020. The same approach is applied to above-the-line and below-the-line packages. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 9. Effect of announced fiscal shocks, interaction with containment measures

	(1)	(2)	(3)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
High State # Fiscal Shock	-0.067		
	(0.155)		
Low State # Fiscal Shock	0.396*		
	(0.180)		
High State # Emergency Lifelines		0.655**	
		(0.250)	
Low State # Emergency Lifelines		-0.272*	
		(0.138)	
High State # Demand Support Measures		-0.759***	
		(0.225)	
Low State # Demand Support Measures		0.971**	
		(0.320)	
High State # Above the line Measures			-0.886***
			(0.219)
Low State # Above the line Measures			1.036***
			(0.364)
High State # Below the line Measures			0.751***
			(0.277)
Low State # Below the line Measures			-0.342*
			(0.159)
Constant	Yes	Yes	Yes
F-test Difference	3.27	5.62*	8.12*
Observations	480	480	480
R-squared	0.505	0.510	0.511
Number of countries	40	40	40

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + F(z_{it})\beta_L Shock_{i,t} + \left(1 - F(z_{it})\right)\beta_H Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}$, $\gamma = 1.5$. z is a country-specific characteristic 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 $F(z_{it})$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country i at month t; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 10. Effect of announced fiscal shocks, interaction with mobility

	(1)	(2)	(3)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
High State # Fiscal Shock	0.408***		
	(0.143)		
Low State # Fiscal Shock	0.245***		
	(0.069)		
High State # Emergency Lifelines		0.139	
		(0.228)	
Low State # Emergency Lifelines		0.588**	
		(0.250)	
High State # Demand Support Measures		0.818	
		(0.497)	
Low State # Demand Support Measures		-0.2739	
		(0.265)	
High State # Above the line Measures			0.764
			(0.496)
Low State # Above the line Measures			-0.302
			(0.275)
High State # Below the line Measures			5.466
			(0.212)
Low State # Below the line Measures			0.582**
			(0.248)
Constant	Yes	Yes	Yes
F-test Difference	1.66	3.63	5.12*
Observations	428	428	428
R-squared	0.635	0.636	0.636
Number of countries	39	39	39

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + F(z_{it})\beta_L Shock_{i,t} + (1 - F(z_{it}))\beta_H Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}$, y = 1.5 . z is a country-specific characteristic 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 $F(z_{it})$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country i at month t; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

ANNEX

Table A1. Effect of announced fiscal measures on manufacturing PMIs, additional controls

VARIABLES	(1) PMI Manufacturing	(2) PMI Manufacturing	(3) PMI Manufacturing	(4) PMI Manufacturing	(5) PMI Manufacturing	(6) PMI Manufacturing
Fiscal Shock	0.183**	0.226***	0.146*	0.209**	0.232**	0.215**
	(0.069)	(0.063)	(0.078)	(0.073)	(0.077)	(0.087)
Containment Measures Index	-5.062*	-9.162**	-17.764***	-13.674***	-3.622***	2.454
	(2.528)	(2.982)	(2.826)	(3.929)	(0.998)	(2.959)
COVID-19 Cases	-0.416**	-1.427***	-0.249	-0.227***	-0.470***	-0.785***
	(0.152)	(0.174)	(0.171)	(0.070)	(0.105)	(0.108)
Consensus Forecasts (lagged)		-1.110***				
		(0.162)				
Policy Rate Change			-0.857***			-1.130***
			(0.182)			(0.188)
Monetary Policy Announcements			0.043			0.113**
			(0.069)			(0.045)
New COVID-19 Fatalities				-1.404**		-0.448
				(0.519)		(0.389)
Retail Mobility					0.155***	0.167***
					(0.016)	(0.019)
Time Fixed Effects	Yes	No	No	No	No	No
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	384	330	238	351	340	208
R-squared	0.788	0.73	0.631	0.681	0.721	0.734
Number of countries	32	30	20	32	31	19

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A2. Effect of announced fiscal measures on Composite Leading Indicator, additional controls

	(1)	(2)	(3)	(3)	(4)	(5)
VARIABLES	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)
Fiscal Shock	0.063**	0.101***	0.105**	0.104*	0.101*	0.122**
	(0.027)	(0.026)	(0.043)	(0.047)	(0.053)	(0.050)
Containment Measures Index	-4.126	-3.210*	-11.318***	-5.330**	-4.432***	-5.513**
	(2.376)	(1.654)	(2.184)	(2.179)	(0.686)	(2.149)
COVID-19 Cases	-0.135*	-0.754***	-0.085	-0.342***	-0.366***	-0.342***
	(0.072)	(0.104)	(0.109)	(0.074)	(0.031)	(0.103)
Consensus Forecasts (lagged)		-0.393***				
		(0.067)				
Policy Rate Change			-0.371*			-0.631*
			(0.203)			(0.311)
Monetary Policy Announcements			0.056**			0.050***
			(0.020)			(0.007)
New COVID-19 Fatalities				-0.415*		-0.295
				(0.224)		(0.276)
Retail Mobility					0.027***	0.026*
					(0.006)	(0.012)
Time fixed effects	Yes		No	No	No	No
Constant	Yes		Yes	Yes	Yes	Yes
Observations	396		288	363	352	253
R-squared	0.663		0.612	0.633	0.622	0.643
Number of countries	33		24	33	32	23

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A3. Effect of announced fiscal measures on unemployment, additional controls

VARIABLES	(1) Unemployment Rate (Change)	(2) Unemployment Rate (Change)	(3) Unemployment Rate (Change)	(4) Unemployment Rate (Change)	(5) Unemployment Rate (Change)	(6) Unemployment Rate (Change)
Fiscal Shock	-0.075***	-0.086**	-0.071**	-0.062***	-0.058***	-0.076**
	(0.014)	(0.036)	(0.028)	(0.018)	(0.017)	(0.027)
Containment Measures Index	-2.818**	-2.391**	-1.765***	-2.316*	-2.015**	-3.219***
	(1.016)	(1.035)	(0.400)	(1.210)	(0.767)	(0.770)
COVID-19 Cases	0.345	0.280*	0.229***	0.131	0.113	0.273***
	(0.200)	(0.128)	(0.060)	(0.098)	(0.094)	(0.070)
Consensus Forecasts (lagged)		0.201***				
		(0.052)				
Policy Rate Change			-1.022			-0.984
			(1.102)			(1.057)
Monetary Policy Announcements			0.089***			0.079***
			(0.023)			(0.024)
New COVID-19 Fatalities				0.293*		0.113
				(0.157)		(0.190)
Retail Mobility					-0.012***	-0.007
					(0.003)	(0.009)
Time FE	Yes	No	No	No	No	No
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	292	225	194	292	292	194
R-squared	0.0739	0.0347	0.0556	0.0286	0.0242	0.0584
Number of countries	30	23	20	30	30	20

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A4. Effect of announced fiscal measures on sovereign CDS spreads, additional controls

	(1)	(2)	(3)	(4)	(5)	(6)
	CDS Spreads	CDS Spreads	CDS Spreads	CDS Spreads	CDS Spreads	CDS Spreads
Fiscal Shock	-0.028**	-0.003	-0.061***	-0.043**	-0.041**	-0.059***
	(0.009)	(0.002)	(0.018)	(0.015)	(0.016)	(0.015)
Containment Measures Index	9.408**	1.138**	11.347**	6.158	6.965**	4.560***
	(3.113)	(0.408)	(3.690)	(3.578)	(2.537)	(1.238)
COVID-19 Cases	-1.276***	-0.025	-0.560*	-0.314	-0.357	-0.266*
	(0.318)	(0.039)	(0.278)	(0.243)	(0.212)	(0.136)
Consensus Forecasts (lagged)		0.053**				
		(0.018)				
Policy Rate Change			7.137***			7.071***
			(1.457)			(2.091)
Monetary Policy Announcement			-0.053**			-0.044***
			(1.458)			(0.005)
New COVID-19 Fatalities				0.320**		1.144***
				(0.138)		(0.107)
Retail Mobility					-0.009	0.022*
					(0.008)	(0.010)
Time fixed effects	Yes	No	No	No	No	No
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	600	341	432	550	538	384
R-squared	0.396	0.0485	0.510	0.548	0.547	0.662
Number of countries	50	31	36	50	49	35

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A5. Effect of announced fiscal shocks on manufacturing PMI, by type of measure

	(1)	(2)	(3)
	PMI Manufacturing	PMI Manufacturing	PMI Manufacturing
Fiscal Shock	0.190**		
	(0.074)		
Fiscal Shock * Emergency Lifelines Dummy		0.183*	
		(0.087)	
Fiscal Shock * Demand Support Dummy		0.197**	
		(0.065)	
Fiscal Shock * Below-the-Line Measures Dummy			0.197**
			(0.065)
Fiscal Shock * Above-the-Line Measures Dummy			0.183*
			(0.087)
Containment Measures Index	-19.780***	-19.767***	-19.767***
	(2.388)	(2.412)	(2.412)
COVID-19 Cases	-0.050	-0.051	-0.051
	(0.197)	(0.198)	(0.198)
Constant	Yes	Yes	Yes
Observations	384	384	384
R-squared	0.648	0.648	0.648
Number of countries	32	32	32

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$ Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. The emergency lifeline (demand-support) dummy is equal to 1 (zero) for any given country in case emergency lifelines (demand-support measures) make up more than 50 percent of its entire fiscal stimulus package in 2020. The same approach is applied to above-the-line and below-the-line packages. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A6. Effect of announced fiscal shocks on CLI, by type of measure

	(1)	(2)	(3)
	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)	Composite Leading Indicator (y-o-y growth)
Fiscal Shock	0.089*		
	(0.043)		
Fiscal Shock * Emergency Lifelines Dummy		0.098	
		(0.059)	
Fiscal Shock * Demand Support Dummy		0.072***	
		(0.018)	
Fiscal Shock * Below-the-Line Measures Dummy			0.077***
			(0.018)
Fiscal Shock * Above-the-Line Measures Dummy			0.095
			(0.057)
Containment Measures Index	-8.538***	-8.551***	-8.545***
	(1.479)	(1.506)	(1.498)
COVID-19 Cases	-0.185**	-0.184**	-0.184**
	(0.067)	(0.069)	(0.068)
Constant	Yes	Yes	Yes
Observations	396	396	396
R-squared	0.602	0.602	0.602
Number of countries	33	33	33

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$ Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. The emergency lifeline (demand-support) dummy is equal to 1 (zero) for any given country in case emergency lifelines (demand-support measures) make up more than 50 percent of its entire fiscal stimulus package in 2020. The same approach is applied to above-the-line and below-the-line packages. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A7. Effect of announced fiscal shocks on unemployment, by type of measure

	(1)	(2)	(3)
	Unemployment Rate (change)	Unemployment Rate (change)	Unemployment Rate (change)
Fiscal Shock	-0.053**		
	(0.017)		
Fiscal Shock * Emergency Lifelines Dummy		-0.210	
		(0.125)	
Fiscal Shock * Demand Support Dummy		0.059***	
		(0.013)	
Fiscal Shock * Below-the-Line Measures Dummy			0.066***
			(0.012)
Fiscal Shock * Above-the-Line Measures Dummy			-0.2154
			(0.126)
Containment Measures Index	-0.685	-0.667	-0.642
	(0.592)	(0.567)	(0.552)
COVID-19 Cases	0.073	0.054	0.047
	(0.094)	(0.086)	(0.083)
Constant	Yes	Yes	Yes
Observations	292	292	292
R-squared	0.0219	0.0295	0.0301
Number of countries	30	30	30

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$ Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. The emergency lifeline (demand-support) dummy is equal to 1 (zero) for any given country in case emergency lifelines (demand-support measures) make up more than 50 percent of its entire fiscal stimulus package in 2020. The same approach is applied to above-the-line and below-the-line packages. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A8. Effect of announced fiscal shocks on sovereign CDS spreads, by type of measure

	(1)	(2)	(3)
	CDS Spreads	CDS Spreads	CDS Spreads
Fiscal Shock	-0.044***		
	(0.009)		
Fiscal Shock * Emergency Lifelines Dummy		-0.064**	
		(0.022)	
Fiscal Shock * Demand Support Dummy		-0.0221	
		(0.020)	
Fiscal Shock * Below-the-Line Measures Dummy			-0.0259
			(0.018)
Fiscal Shock * Above-the-Line Measures Dummy			-0.060**
			(0.021)
Containment Measures Index	10.261***	10.283**	10.278**
	(3.293)	(3.323)	(3.319)
COVID-19 Cases	-0.586*	-0.588*	-0.588*
	(0.294)	(0.297)	(0.297)
Constant	Yes	Yes	Yes
Observations	600	600	600
R-squared	0.388	0.388	0.388
Number of countries	50	50	50

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$ Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. The emergency lifeline (demand-support) dummy is equal to 1 (zero) for any given country in case emergency lifelines (demand-support measures) make up more than 50 percent of its entire fiscal stimulus package in 2020. The same approach is applied to above-the-line and below-the-line packages. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A9. Effect of announced fiscal shocks on industrial production, by type of measure, higher threshold

	(1)	(2)	(3)
	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)	Industrial Production (y-o-y growth)
Fiscal Shock	0.254***		
	(0.057)		
Fiscal Shock * Emergency Lifelines Dummy		0.285**	
		(0.120)	
Fiscal Shock * Demand Support Dummy		-0.286	
		(0.364)	
Fiscal Shock * Below-the-Line Measures Dummy			0.420**
			(0.137)
Fiscal Shock * Above-the-Line Measures Dummy			-0.075
			(0.090)
Containment Measures Index	-21.212***	-21.105***	-21.280***
	(3.497)	(3.599)	(3.549)
COVID-19 Cases	-0.928***	-0.932***	-0.913***
	(0.194)	(0.196)	(0.193)
Constant	Yes	Yes	Yes
Observations	480	480	480
R-squared	0.565	0.566	0.567
Number of countries	40	40	40

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + \beta LL_{i,t} + \gamma DS_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$ Where $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. $LL_{i,t}$ is an emergency lifeline dummy interacted by the fiscal shock to represent an emergency lifelines package, while $DS_{i,t}$ is demand-support dummy interacted by the fiscal shock to represent a demand-support measures package. The emergency lifeline (demand-support) dummy is equal to 1 (zero) for any given country in case emergency lifelines (demand-support measures) make up more than 60 percent of its entire fiscal stimulus package in 2020. The same approach is applied to above-the-line and below-the-line packages. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A10. Effect of announced fiscal shocks, by country and pandemic characteristics, higher thresholds

	(1)	(2)	(3)
	Containment Measures Industrial Production (y-o-y growth)	**Mobility** Industrial Production (y-o-y growth)	**Debt-to-GDP** Industrial Production (y-o-y growth)
High State * Fiscal Shock	0.658**	0.321**	0.617***
	(0.245)	(0.101)	(0.113)
Low State * Fiscal Shock	0.132	0.251*	0.128
	(0.084)	(0.130)	(0.076)
Containment Measures Index			
	-2.370***	-1.061***	-0.938***
COVID-19 Cases	(0.205)	(0.198)	(0.204)
		-22.436***	-21.749***
		(3.836)	(3.630)
Constant	Yes	Yes	Yes
Observations	480	480	480
R-squared	0.566	0.575	0.575
Number of countries	40	40	40

Note: results reported are based on a sample of 52 countries using daily data from January 1, 2020 to December 30, 2020. Estimates are based on $\Delta Y_{i,t} = \alpha + u_i + F(z_{it})\beta_L Shock_{i,t} + \left(1 - F(z_{it})\right)\beta_H Shock_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}$, with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}$, y = 1.5 . z is a country-specific characteristic 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 $F(z_{it})$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime if $F(z_{it})$ is higher than the median country/pandemic characteristic. $\Delta Y_{i,t}$ is the growth rate of industrial production, manufacturing PMI, the CLI, the unemployment rate, or sovereign CDS spreads of country *i* at month *t*; $Shock_{i,t}$ denotes the fiscal shock, u_i are country-fixed effects to account for time-invariant specific factors; $X_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table A11. Relationship between GDP and Industrial Production

	(1)	(2)
	Industrial Production (y-o-y)	Industrial Production (y-o-y)
GDP Growth (y-o-y)	0.990***	1.200***
	(0.113)	(0.203)
Constant	-0.017***	-0.021***
	(0.002)	(0.007)
Time Fixed-Effects	No	Yes
Observations	291	291
R-squared	0.258	0.303
No. of countries	60	60

Note: results reported are based on a sample of 60 countries using quarterly data from 2018Q1 to 2019Q4. Estimates are based on $\Delta IP_{i,t} = \alpha + u_i + \beta \Delta GDP_{i,t} + \varepsilon_{i,t}$ Where $\Delta IP_{i,t}$ is the growth rate of industrial production of country *i* at quarter *t*; $\Delta GDP_{i,t}$ is the growth rate of GDP of country *i* at quarter *t*; u_i are country-fixed effects to account for time-invariant specific factors, and $\varepsilon_{i,t}$ is the error term. Driscoll-Kraay standard errors are presented in parentheses. ***, **, * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

DATA ANNEX

A. Fiscal Policy Measures

The main source of the data is the *Yale's COVID-19 Financial Response Tracker (CFRT).*[16] The database reports the policy actions for over 180 countries during 2020. The CFRT provides for each policy action when information is available the following: i) the adoption/proposal date, ii) the implementation date, iii) the institutional role , iv) the policy tool used, v) the policy instrument, vi) the magnitude, vii) the order of magnitude, viii) the metric, ix) notes on the policy action, and x) links related to the policy action. The information from the Yale database is supplemented by, and cross-checked with, announcements provided by the *IMF Policy Tracker*, the *OECD Country Policy Tracker* and newspaper reports. On several instances, the numbers quoted by the dataset do not match what is reported by the IMF policy tracker and other resources. On such occasions, we extensively research the policy announcements through browsing newspaper reports and announcement links in order to report our best assessment of the date, size, and type of announced measure. Figure D1 provides a snapshot of database. We follow the following steps to create the fiscal database:

Country selection: we refine the selection of countries to 52 countries for which data on industrial production and PMI manufacturing is available. Countries included in the sample are reported in Table D1.

Institutional role: we look at the institutional role of each policy action. Institutional roles refer to the institutional authorities responsible for the policy actions proposed or implemented. Three

[16] https://som.yale.edu/faculty-research-centers/centers-initiatives/program-on-financial-stability/covid-19-crisis

main authorities are responsible for the policy actions proposed: fiscal authority, monetary authority, and a regulatory authority. To build the fiscal database, we use all policy actions proposed by the country's fiscal authority. Oftentimes, the institutional role of a policy action is reported under fiscal and monetary authorities, fiscal and regulatory authorities, or all fiscal, monetary, and regulatory authorities. In those instances, we carefully assess the policy action and omit it from the fiscal database in case we deem it does not clearly qualify as a fiscal action.

Policy tools: we examine the policy tools which identify each policy action. Policy tools can be largely grouped under 8 sub-categories: i) asset purchases, ii) asset guarantees, iii) capital injections, iv) tax relief measures, v) grants, vi) payment forbearances, vii) loans and viii) credit guarantees. For each of the measures, we review the accompanying notes as well as the links provided to ensure it is being appropriately labelled and change the labelling when we deem it inaccurate. In the instances that policy actions are reported as a mix of policy tools, we review the notes and links provided and split the policy tool entry into two or more, while reporting the appropriate amount for each. Measures which are unidentified or labelled as "other" are also examined in the same fashion. In case the reported policy action is a bond issuance, or a budget increase, we omit it from the database as to avoid double-counting. We also remove from the database any IMF or World Bank provided funding for which we do not know the intent of the use, in order to avoid double-counting as well.

Policy instruments: beyond filtering policy tools, we examine each policy action to identify which policy instrument was used. Namely, we read through the explanation notes and the links provided for announcements to identify the purpose of each policy action used. For instance, if the policy action provides cash transfers to the population, then the identified policy instrument is "cash transfers". In case healthcare spending is announced to combat the pandemic, the policy instrument is labelled as “healthcare spending”. If liquidity measures are provided to certain sectors (airline carriers, hotels, museums, etc.), we identify the policy instrument as “sector support”. We repeat this step for each measure included for the 52 countries in our database. This step is necessary to help us classify policy actions in the steps to come.

Classification by type of measure: a key contribution of our database is the classification of each policy action for the 52 countries in our database by type of measure. Namely, we identify two main types of measures: demand-support measures and emergency lifelines (IMF 2020). Demand-support measures are used to boost demand and households/firms’ disposable income and can be grouped into two categories. The first is spending-side measures to boost households’ disposable income, which include wage subsidies and targeted transfers to households, enhancement of unemployment benefits, paid sick leave and support to parents for school closures. The other is revenue-side measures to alleviate losses to firms and households, and include sectoral support measures, reduction of social security contributions, tax relief measures for firms and households, and deferrals of tax and social security payments for firms and households. Meanwhile, emergency lifelines refer to liquidity measures which provided sustained cashflow support to firms and households, especially during the lockdown phase of the pandemic, when firms needed to shut down production in order to maintain social distancing. Such measures include loans to firms and households, umbrella guarantees, government provisions of loans, and equity injections.

Classification by accounting principle: the second classification is from an accounting standpoint: we record each policy action as “above-the-line” or “below-the-line”. We follow the IMF’s fiscal monitor classification by recording above-the-line measures as those which are “reflected in the fiscal balance, government debt, and increased borrowing needs in the short term” (IMF 2020). Such measures would include additional spending such as health services and unemployment benefits, grants and transfers, tax cuts or tax relief measures, as well as deferrals of tax payments or social security contributions (payment forbearances). Meanwhile, below-the-line measures are defined as those which have no upfront impact on the fiscal deficit but can increase debt or liabilities in the long-term. Those involve the creation of assets, such as loans or equity injections to firms, given that those have little or no upfront impact on the fiscal deficit in the short-term, but can increase debt or reduce liquidity. In addition, government guarantees to banks, firms and households are also considered below-the-line, given that they create a contingent liability to the government. Based on these definitions, we consider grants, tax relief, and payment forbearance measures as above-the-line measures, and the rest (loans, capital injections, asset purchases and guarantees, credit guarantees) as below-the-line measures.

B. Monetary Policy Measures

We collect data on monetary policy measures to control for the possibility that fiscal announcements are correlated to such measures and could result in omitted variable bias. We collect monthly data for key policy rates across 38 countries from January 2020 to December 2020. Data is sourced from Haver Analytics. We also use Yale's CFRT to control for all announcements and policy actions by monetary authorities worldwide beyond policy rate actions during 2020. Such measures will include whichever capital and equity injections, asset purchases, loans, credit guarantees, or other payment forbearances were provided by a country's monetary authority during the COVID-19 crisis, and therefore not reported as a fiscal policy measure. Data coverage is on a daily frequency, from January 1 to December 30, 2020, for the 52 countries in our dataset.

C. Indicators of economic activity

We use several indicators of economic activity: (i) to purge the fiscal announcements from any predictable components; and to (ii) examine the effect of fiscal policy announcements.

Daily and weekly indicators

- Nitrogen Dioxide (NO_2) emissions. We use daily data on Nitrogen Dioxide (NO_2) emissions from the Air Quality Open Data Platform of the World Air Quality Index (WAQI). Data available on WAQI is collected from countries' respective Environmental Protection Agencies (EPA). The database for NO_2 levels covers 62 countries in total, with coverage beginning from January 1, 2020. The data is based on the median level of emissions reported by city-specific stations, and is provided in US EPA standards, in parts per billion (ppb).

- Mobility Trends. We collect data on retail mobility from Google Mobility Reports. The reports provide daily data by country and highlight the percent change in visits to places related to retail activity (restaurants, cafes, shopping centers, movie theaters, museums, and libraries). The data is reported as the change relative to a baseline value for that corresponding day of the week, and the baseline is calculated as the median value for that corresponding day of the week, during the 5-week period between January 3rd and February 6th, 2020. Daily data are available for over 130 countries, with coverage beginning from February 15, 2020.

- Containment measures. We compute a Stringency Index using Oxford's COVID-19 Government Response Tracker (OxCGRT) as a proxy for containment measures. OxCGRT collects information on government policy responses across eight dimensions, namely: (i) school closures; (ii) workplace closures; (iii) public event cancellations; (iv) gathering restrictions; (v) public transportation closures; (vi) stay-at-home orders; (vii) restrictions on internal movement; and (viii) international travel bans. The database scores the stringency of each measure ordinally, for example, depending on whether the measure is a recommendation or a requirement and whether it is targeted or nation-wide. We normalize each measure to range between 0 and 1 to make them comparable, and then compute and aggregate the Stringency Index as the average of the sub-indices, again normalized to range between 0 and 1. The data start on January 1, 2020 and cover 176 countries/regions.

- COVID-19 infections. Data on COVID-19 infections are collected from the COVID-19 Dashboard from the Coronavirus Resource Center of Johns Hopkins University. Coverage begins from January 22, 2020. It provides the location and number of confirmed cases, deaths, and recoveries for 211 affected countries and regions.

- Flights. Flight data are collected from FlightRadar24, which provides real-time information on worldwide flights from several data sources, including automatic dependent surveillance-broadcast (ADS-B), (Multilateration) MLAT and radar data. The database covers international and domestic inbound and outbound flights data for over 200 countries, 84 of which are used in our analysis. Data coverage is on a daily frequency and begins on January 1, 2020. Data for total flights is calculated by summing daily domestic and international flights.

- Bilateral exchange rates. Daily data for bilateral exchange rates at closing price are collected for 42 countries from Bloomberg, from January 1, 2020 to December 31, 2020.

- Stock market indices Daily data for country-specific stock market indices at closing price are collected for 42 countries from Bloomberg, from January 1, 2020 to December 31, 2020.

- OECD activity tracker. We use weekly data for the OECD tracker of GDP growth, a real-time high-frequency indicator of economic activity based on machine learning techniques and

Google Trends data. The tracker proxies the percent change in weekly GDP compared to pre-crisis trends for 46 countries, from January 1,2020 to December 31, 2020.[17]

Monthly indicators

- Industrial Production Indices. We used data on industrial production indices for 40 countries from Haver Analytics. Data is at a monthly frequency, from January 2019 to December 2020. Industrial production indices are converted to growth rates on a year-on-year basis.

- Manufacturing Purchasing Managers' Indices (PMIs). We supplement industrial production data with manufacturing PMIs for 32 countries from Haver Analytics. Data coverage is on a monthly frequency, from January 2019 to December 2020. Manufacturing PMIs are also converted to growth rates on a year-on-year basis.

- Composite Leading Indicator (CLI). CLIs are collected from the OECD database for 33 countries from January to December 2020 and provide signals of turning points in business cycles. They reflect short-term movements in qualitative rather than quantitative terms.[18]

- Sovereign Credit Default Swaps (CDS) spreads. Sovereign CDS spreads are collected for 50 countries on a daily basis from Bloomberg. Given that sellers of CDS must compensate buyers in the event of a debt default or other credit events, the spreads on these swap agreements act

[17] https://www.oecd.org/economy/weekly-tracker-of-gdp-growth/

[18] CLIs for any given country is composed from a set of selected economic indicators whose composite provides a robust signal of future turning points (using a simplified version of the Bry-Boschan algorithm). The selected indicators are filtered to remove factors such as seasonal patterns, outliers, trends etc. and normalized. The final CLI is aggregated using equal weights. See OECD (2021) for more details.

as a proxy for confidence in the sovereign, with lower spreads reflecting higher confidence. Coverage is from January to December 2020.

- Unemployment rate. Unemployment rates are collected from Haver Analytics, CEIC, and national sources for 30 countries, on a monthly frequency, from January to December 2020.

- Consensus Forecasts. Monthly data on consensus forecasts on GDP growth (which are polled monthly based on the views and forecasts of more than 700 economists) is sourced from *ConsensusEconomics*, with coverage from January to December 2020 for 85 countries.

D. Other data

Additional data on country characteristics, used to construct interaction dummies, such as income levels (AE vs. EMDE), level of public debt and trade openness are drawn from the IMFs World Economic Outlook Database. We use data as of end-2019.

Figure D1. Snapshot of Database

Proposal Date	Policy Tool	Policy Instrument	Classification 1	Classification 2	Magnitude (Billion USD)	Notes
3/13/2020	Grants	Healthcare Spending	above-line	Demand-support	50	The President's national emergency declaration will make up to $50 billion… for healthcare providers and facilities...
3/17/2020	Credit guarantees	SMEs	below-line	Emergency Lifelines	10	…to support the flow of credit to households and businesses… provides $10 billion of credit protection…
3/27/2020	Grants	Cash transfers	Above-line	Demand-support	293	Part of Package- …provides to households of up to $1,200 per adult for individuals whose income was less than … or up to $3,400 for a family of four.
4/2/2020	Grants	Infrastructure spending	Above-line	Demand-support	25	Part of Package- …today announced a total of $25 billion USD in funding to help the Nation's public transportation systems…
9/29/2020	Lending	Sector support	Below-line	Emergency Lifelines	7.5	The… department of the Treasury announced that it has closed loans to seven large passenger air carriers… reallocation of funds will be subject to a loan concentration limit of $7.5 billion…

Note: this figure provides a screenshot of the main characteristics of the CRFT. In addition to reviewing and amending policy tools when necessary, authors identified policy instruments, and the classification for each entry, based on notes and texts provided from the links related to each policy announcement.

Table D1. List of countries

Argentina	Hungary	Russia
Australia	India	Serbia
Austria	Indonesia	Slovenia
Belgium	Ireland	Spain
Bosnia and Herzegovina	Italy	Sri Lanka
Brazil	Japan	Switzerland
Bulgaria	Kazakhstan	Taiwan Province of China
Canada	Kenya	Thailand
Chile	Korea	Turkey
China	Latvia	United Kingdom
Colombia	Lithuania	United States
Czech Republic	Malaysia	Vietnam
Denmark	Mexico	
Egypt	Netherlands	
Estonia	Norway	
Finland	Philippines	
France	Poland	
Germany	Portugal	
Greece	Qatar	
Hong Kong SAR	Romania	