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The Impact of the IMF's COVID-19 Support to Developing and Emerging Economies

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ABSTRACT: We construct a high-frequency dataset that combines information on all IMF lending and proxies of monthly economic activity during the first two years of the COVID-19 pandemic (2020–21). Using this novel dataset and standard econometric techniques we find a positive and significant marginal effect of IMF financing on economic activity in low-income countries (LICs) and emerging market economies. We also present tentative evidence that IMF financing may have helped economic outcomes by easing fiscal budget constraints, allowing for larger government spending in response to the pandemic. Overall, this evidence suggests that IMF financing helped lessen the negative impacts of the pandemic on economic activity, especially in LICs.

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WORKING PAPERS

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Prepared by Sumin Chun, Karmen Naidoo and Nelson Sobrinho[1]

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Glossary

CCRT	Catastrophe Containment and Relief Trust
CSIS	Center for Strategic and International Studies
DNB	Day Night Band
DOTS	Direct of Trade Statistics
DSBB	Dissemination Standards Bulletin Board
DSSI	Debt Service Suspension Initiative
ECF	Extended Credit Facility
EFF	Extended Fund Facility
EMEs	Emerging Market Economies
FE	Fixed Effects
GDP	Gross Domestic Product
GRA	General Resources Account
ICT	Information and Communications Technology
IFIs	International Financial Institutions
IFS	International Financial Statistics
IMF	International Monetary Fund
LICs	Low-Income Countries
MDBs	Multilateral Development Banks
PRGT	Poverty Reduction and Growth Trust
RCF	Rapid Credit Facility
RFI	Rapid Financing Instrument
SBA	Stand-By Arrangement
SCF	Standby Credit Facility
SDR	Special Drawing Rights
TWFE	Two-Way Fixed Effects
UCT	Upper Credit Tranche
VIIRS	Visible and Infrared Imaging Suite
WB	World Bank
WGI	Worldwide Governance Indicators

Executive Summary

We estimate the impact of IMF pandemic-related lending on the economic performance of a comprehensive set of low-income countries (LICs) and emerging market economies (EMEs) using a newly compiled dataset that covers all IMF lending facilities and several high-frequency proxies of economic activity.

Exploiting variation in amounts of IMF financing received by countries during the pandemic, we find that IMF financing had a significant and positive impact on key proxies of economic activity by the end of 2021, including two indirect measures (mobility, nighttime luminosity) and one direct measure comprising high-frequency indicators of aggregate demand and production. The size of the effect is economically non-negligible. Our back-of-envelope calculations suggest that an illustrative 10-percent increase in IMF financing is associated with up to 0.2 percentage point higher level of GDP in IMF-funded countries relative to unfunded countries, by the end of 2021. The economic effect is strongest in the poorest IMF members that received concessional financing. We further find some evidence of a possible positive effect of IMF lending on government spending on pandemic responses, in line with the observed use of IMF lending, especially by LICs, to ease fiscal financing pressures. Our baseline results hold across different econometric specifications and when including various control variables.

The evidence provided in this paper suggests that IMF interventions can play a positive role in supporting economies through acute crises — an issue that continues to be debated in the literature. We provide evidence that IMF interventions, which included sizeable budgetary support in times of a health crisis, can be effective. The question of whether IMF interventions are efficient or at the optimal scale, and whether the short-term effects that we estimated in this paper also hold over longer horizons, remain to be explored.

Introduction

The COVID-19 pandemic is an unprecedented global health and economic shock, for which many countries were not well prepared. It is estimated that the pandemic killed more than 6 million people worldwide in the first two years and could cost about US$13.8 trillion in cumulative output loss globally through to 2024 (Agarwal et al., 2022; IMF, 2022). The IMF's World Economic Outlook (IMF, 2022) estimated that world output shrank by 3.1 percent in 2020, the sharpest decline in recent history and much larger than during the 2008–09 global financial crisis. In the case of poor countries, the adverse effects of the pandemic extend far beyond the economic losses, to include adverse distributional consequences since the pandemic disproportionately affected women, low-income and migrant workers, and other vulnerable groups (Miguel and Mobarak, 2021).

Early in the pandemic, most countries around the world implemented some form of localized or national lockdown measures to slow down the spread of the virus and buy time for governments to prepare their respective health systems. Along with the negative health effects of COVID-19, the lockdowns were economically costly and had major negative impacts on employment and earnings. Further, local and global supply chain bottlenecks led to reduced supply of imported goods and higher prices. Across developing and emerging economies, governments responded with different forms of social assistance and support for firms. However, many of these economies remained particularly vulnerable due to weaker health systems, a lower proportion of jobs that can be done remotely, weaker information and communication technology infrastructure, and stronger reliance on imported goods, compared to most advanced economies.

To help cope with the extraordinary effects of the pandemic, many developing and emerging countries turned to the IMF and other international financial institutions (IFIs) for emergency financing. The IMF swiftly provided financial support to its members at an unprecedented scale. In the case of low-income countries (LICs) that are eligible for concessional financing from the Poverty Reduction and Growth Trust (PRGT), the IMF provided financing to 53 of 69 eligible LICs during 2020–21. This totaled about US$18 billion in new concessional lending commitments, about five times the pre-pandemic annual average, and about US$24 billion if we also consider regular (non-concessional) lending to LICs from the General Resources Account (GRA). Further, 35 of 80 emerging market economies (EMEs, mostly middle-income countries) in our sample that can borrow from the GRA, also received support, totaling about US$150 billion, including under precautionary arrangements.[1] IMF lending was mostly used by governments to support public health measures, mitigate the effects of the economic downturn that resulted from national containment measures and global supply chain disruptions, as well as rebuild external buffers.

[1] The IMF's concessional lending facilities are the Rapid Credit Instrument (RCF), the Extended Credit Facility (ECF), and the Standby Credit Facility (SCF); whereas non-concessional lending instruments under the GRA include the Rapid Financing Instrument (RFI), the Extended Fund Facility (EFF), the Stand-By Arrangement (SBA), the Flexible Credit Line (FCL), and the Precautionary and Liquidity Line (PLL). The RCF and RFI provide rapid financing with limited conditionality to address urgent balance of payments needs when multiyear arrangements are not feasible or not needed; the ECF, SCF, EFF, and SBA are drawing instruments typically used in multiyear IMF-supported programs, and which use also requires demonstration of balance of payments needs amongst other qualification criteria; whereas the FCL and PLL are precautionary instruments for EMEs (the SCF and the SBA can also be provided on a precautionary basis). See IMF Lending for an overview of IMF lending facilities.

This paper estimates the impact of countries' access to IMF funding under its various lending facilities on economic activity, and government spending across a large sample of LICs and EMEs, following the onset of the pandemic. To this end, we construct a novel, monthly database that combines information on all IMF lending during the pandemic with high-frequency proxies of economic activity, along with important controls related to the severity of the pandemic and other sources of financing.

Our empirical analysis starts with an overview of the type and magnitude of IMF lending to LICs and EMEs in 2020–21. We initially present descriptive analysis comparing proxies of economic activity in countries that accessed IMF financing to countries that did not. This exercise provides the first indication that IMF-funded countries on average experienced a faster economic recovery compared to unfunded countries.

Next, using a two-way fixed effects model, we estimate the marginal effect of IMF support on economic activity in LICs and EMEs during 2020–21. We find a statistically significant positive impact of IMF financing on our sample of countries' economies across all proxies of economic activity. The effect is strongest in LICs, for which we found that the marginal effect is statistically and economically higher than for higher-income countries. Back-of-envelope calculations suggest that an illustrative 10-percent increase in IMF financing is associated with up to an 0.2 percentage point greater improvement in GDP levels (or smaller loss) by the end of 2021 in IMF-funded countries on average, relative to countries that did not receive (or receive less) IMF funding. This indicates a non-trivial economic impact of IMF financing. As a potential explanation for how IMF financing affects economic outcomes, we conjecture that governments were able to spend more resources on the COVID response, thus helping a faster economic recovery. We present some support for this narrative, finding a weak but positive association between COVID-related government expenditures and IMF financing.

Our baseline results are robust to controlling for common time trends across countries, the progression of the pandemic, lockdown measures, and availability of additional financing from other IFIs and own reserves. We also explore specifications that use alternative measures of IMF lending and find results that are of a similar sign and magnitude to the baseline. These tests allow us to conclude that our baseline findings are not an artifact of the data or econometric specifications used.

Our contributions to the literature are threefold. First, to our knowledge, we are the first to analyze the impact of IMF's lending on economic activity in LICs and EMEs during the COVID-19 pandemic. We document the amount of IMF and other IFI support and economic performance for a comprehensive set of developing and emerging economies and assess whether IMF funds helped support economic activity. Recent research estimates that in the first year of the pandemic, larger output losses were experienced by countries with lower GDP per capita and lower fiscal stimulus (Furceri et al, 2021).[2] The pandemic also negatively affected domestic savings in developing countries, which are a key source of financing for supporting the post-pandemic economic recovery and achieving longer-term development goals. Based on a sample of Sub-Saharan African countries, Loko et al (2022) find that private savings rate declined in LICs during the pandemic, in sharp contrast with the behavior observed in advanced economies.

[2] Along with those countries with higher pre-crisis growth, more stringent containment, higher per capita deaths, more liberalized financial markets, higher tourism dependence, higher social fractionalization, and more democratic regimes (Furceri et al, 2021).

Furthermore, richer countries and countries with a better sovereign credit rating have announced larger fiscal policies in response to COVID-19 than poorer countries or those with a lower credit rating (Benmelech and Tzur-Ilan, 2020). Taken together, this early evidence suggests that developing countries and emerging markets were particularly vulnerable during the COVID-19 crisis due to their constrained ability to announce large fiscal response packages, without external financing assistance.

Second, we contribute to the larger literature on the impact of IMF interventions over different periods of time. The impact of IMF interventions on macroeconomic outcomes at the country level has been subject to much debate in the theoretical literature.[3] Empirical evidence on the impact on macroeconomic stability and on growth and development outcomes has been mixed. A strand of the literature finds that IMF programs are associated with short term improvements in macroeconomic outcomes and the external balance (Atoyan and Conway, 2006; Gunduz, 2016); lower likelihood of currency and banking crises in developing countries (Dreher and Walter, 2010; Bicaba et al, 2014; Papi et al, 2015); stronger financing support from the official sector and reduced macroeconomic adjustment (de Resende and Takagi, 2018); and improved quality of economic governance (Honda, 2008). But another strand finds that IMF programs may succeed because of a country's economic fundamentals and the government's ability to make credible commitments to reforms and not necessarily because of the IMF's "seal of approval" (Mody and Saravia, 2003). Furthermore, studies have found that IMF programs may only lead to short-lived positive impacts on economic growth (Atoyan and Conway, 2006); and have neutral or even temporary negative impact on poverty and inequality (Hajro and Joyce, 2009; Oberdabernig; 2013; Bird et al, 2021).[4] Therefore, no clear consensus has yet been reached in the literature.

A key challenge in estimating the impact of IMF programs is the inherent issue of selection bias, since countries that enter IMF programs are typically facing balance of payments difficulties, which makes choosing appropriate counterfactual countries a challenge.[5] In the current context, selection bias is less severe since the COVID-19 pandemic affected all countries and in a synchronous manner. The remaining selection problem in countries that decided to seek financing from the IMF (countries in most need for funding) is addressed by controlling for key variables that represent the demand for financing and the availability of funding from other sources that would plausibly affect the decision to seek IMF loans. As such, our findings present complementary evidence on the role of IMF interventions during crisis times.

Third, we explore several high-frequency indicators of domestic economic activity, including traditional and less traditional but increasingly used measures. This approach considerably mitigates problems related to lack of direct macroeconomic indicators at higher frequencies in EMEs and especially in LICs.

[3] Some argue that IMF interventions can reduce the probability of crises ex ante and increase economic efficiency ex post (e.g., Sachs, 1995; Fischer, 1999). The IMF is also seen as a delegated monitor mediating between the country seeking financing support and international investors, thereby enhancing the country's access to the international capital markets (e.g., Tirole, 2002). However, critics have doubted the positive effect of IMF as an international lender of last resort, arguing that the IMF has limited 'fire power' in practice. In turn, this could lead to self-fulfilling speculative runs and costly debt defaults (e.g., Zettelmeyer, 2000; Jeanne and Wyplosz, 2001); and create moral hazard problems for both the debtor country and creditors, when crises are triggered by fundamental shocks and policy mismanagement (e.g., Meltzer Commission, 2000).

[4] IEO (2021) also discuss the lack of consensus in the literature about the impact of IMF lending on economic growth and developmental outcomes.

[5] To mitigate reverse causality problems and facilitate construction of counterfactuals, Newiak and Willems (2017) apply a Synthetic Control Method to IMF programs that do not involve any financing (these are typically implemented by non-crisis countries). They find that treated countries experience faster GDP growth, lower inflation, and stronger foreign direct investment.

Our non-traditional measures include nighttime lights and mobility, whereas the traditional ones include monthly indicators of aggregate demand and production, amongst others.

To our knowledge, we are the first to take advantage of nighttime lights and mobility data to study the impact of IMF pandemic-related lending on the real economy. Nighttime lights have been increasingly used in the literature as a proxy for economic and social outcomes, including GDP growth (Beyer et al, 2022; Martínez, 2022), living standards (Mamo et al, 2019), informality (Medina et al, 2017), and local economic development (Michalopoulos and Papaioannou, 2014).[6] The newly available mobility data based on cell phone usage has been used to assess the impact of lockdown measures during the pandemic (Sears et al, forthcoming; Goolsbee and Syverson, 2021). To complement this data, we construct a dataset of economic activity indicators, consisting of more traditional measures such as direct estimates of quarterly GDP, monthly industrial production, and monthly real imports. While the type of indicator varies across countries, to our knowledge they are the best available direct proxies compiled by country authorities (i.e., national central banks and statistical agencies).

The paper is structured as follows. Section II describes the methodology and data. Section III provides an overview of IMF lending during the pandemic as well as a cursory overview of lending from other large multilateral sources. This section also presents a descriptive analysis and key stylized facts. Section IV presents the empirical findings and robustness tests. Section V concludes.

Methodology and Data

Methodology

We use a two-way fixed effects model with a treatment variable to study the impact of IMF lending during the first two years of the COVID-19 pandemic. This approach allows us to account for the staggered timing of IMF funding approvals across countries, as well as to compare pre- and post-financing outcomes in key economic variables at the country-level, considering initial conditions (i.e., pre-pandemic trends) in outcome variables.

We estimate the following two-way fixed effects model (TWFE) with IMF funding as the treatment variable:

$$y_{it} = \alpha_i + \tau_t + \beta Fund_{it} + \gamma X_{it} + \epsilon_{it}$$

The outcome variable of interest, y_{it}, is an indicator of economic activity which we describe in detail in the following section. Country fixed effect α_i controls for unobserved characteristics of the country that determines the persistent level of outcome variable. Time (i.e., month) fixed effect τ_t controls for common time trends. This is an especially important control given that the pandemic hit all countries at the same time, creating a distinct and common time trend across countries. $Fund_{it}$ is the treatment variable that represents the amount and timing of IMF funding received by treated countries. In our baseline

[6] Gibson et al (2020) provide a survey of recent studies in this area.

specification, it is measured by the log of cumulative IMF disbursements received by each country. This choice of treatment variable has two advantages: first, it acts as an indicator of the timing of treatment, taking value 0 before the first disbursement and a positive value after the first disbursement; and second, different from the binary post-indicator, it embodies information on the size of treatment. The magnitude of treatment is key in our analysis given the large observed variation of IMF funding amount across countries. Using the variation in the amount allows to compare between funded countries and avoids comparing countries that were never financed, thus mitigating selection into treatment. Differentiating between smaller and larger financing also uncovers some of the heterogeneity in economic effects. This definition also allows for multiple treatments for a single country, reflecting the fact that many countries in our sample received more than one IMF disbursements during 2020–2021.

The main parameter of interest, β, measures the marginal effect of IMF financing on economic activity, conditional on the covariates and common time trends. Differences in economic outcomes across countries that received various amounts of IMF financing identifies β. Identifying variation includes the difference between countries that receive large IMF disbursements versus countries that received small or no funding.

One challenge we face is the potential of an omitted variable driving both the selection into treatment and economic outcome variable of interest. For example, poorer countries with limited access to liquidity may be more likely to approach the IMF for emergency financing, and their economic recovery may be faster. While country fixed effects partially address this, we also address this issue by including adequate time-varying covariates in X_{it}. The severity of the pandemic and intensity of lockdowns control for the progression of the pandemic and the speed of recovery. We also control for the size of other available financing, including reserves and funds received from other IFIs. We also present additional regressions where we control for group-specific time trends, allowing for differential time trends across groups of countries with varying levels of income and governance. Under the assumption that income is correlated with the underlying omitted variable, this approach draws comparison between a more homogeneous set of countries in terms of path of economic outcomes.

Another challenge to our estimation approach is that two-way fixed effects with heterogeneous treatment effects may incorrectly estimate average treatment effects (de Chaisemartin and D'Haultfoeuille, 2020). The treatment effect is plausibly heterogeneous over time and countries. The effect of the immediate availability of funds will vary at different stages of the pandemic, and countries are likely to have varying degrees of demand and the ability to utilize the obtained funds. Further, IMF lending was approved at different times across countries and including multiple disbursements as separate treatment events introduces staggered timing within country, creating a similar econometric problem (de Chaisemartin and D'Haultfoeuille (2022) discuss this literature in more detail). We acknowledge this potential problem and carefully designed a robustness check that defines the treatment as the sum of disbursements made during April–June of 2020 and eliminates countries that received additional IMF financing thereafter. By collapsing the variation in the timing of the disbursements, this exercise limits comparisons between countries that received financing earlier versus later and instead focuses on differences between treated and never treated countries, which is closer to a standard differences-in-differences approach (in spirit of Callaway and Sant'Anna, 2021).

Data

We construct a novel monthly dataset of IMF lending, various high-frequency indicators of economic activity, and other important covariates, drawing from several data sources. Our regression analysis relies on monthly data, but we also use yearly information in the case of a few covariates for which monthly data is not readily available.[7] Annex I describes in detail the data used in the descriptive analysis and regressions.

We analyze 134 IMF member countries, consisting of all developing and emerging economies excluding eight higher income economies with per capita GDP greater than US$20,000 and 13 fragile economies. This exclusion is intended to mitigate selection bias regarding the control group (e.g., some countries did not immediately meet the qualification criteria for IMF assistance due to for instance, high debt vulnerabilities and/or political constraints). Table AI.1 shows the full list of countries used in this paper.

For IMF lending, we use detailed data from internal repositories on both commitments and disbursements.[8] This covers all commitments and disbursement to any IMF member that requested financing support during the pandemic through its various lending facilities. We include all types of IMF facilities, except in the case of precautionary arrangements, for which we only include the amount effectively drawn as the disbursement amount, not the entire amount available under the arrangement. The original data is conveniently aggregated to monthly frequency. In our selected sample of 134 LICs and EMEs, 83 received IMF financing during the pandemic and 51 did not (Table 1).

Table 1: Countries that Received Pandemic-Related Support and Control Group, 2020–2021

Country Category	Multiyear Program Financing	Emergency Financing	Program and Emergency Financing	None (Control Group)	All
PRGT-only	1	22	16	6	45
Blender[1]	1	7	6	5	19
GRA-only	6	17	7	40	70
All	8	46	29	51	134

[1] Better off LICs, classified as Blenders, typically access PRGT and GRA resources at a 1:2 ratio.

In terms of borrowing characteristics for IMF lending purposes, our sample includes 64 LICs that are eligible for concessional financing (PRGT-only and Blender) and 70 EMEs that are only eligible for non-concessional financing from the GRA. During 2020–21, but especially in the early stages of the pandemic in 2020, emergency financing was the prevalent form of IMF lending: of the 83 countries that received some form of IMF financing support, 75 received emergency financing, with higher incidence amongst PRGT-eligible countries (80 percent) compared to GRA countries (34 percent). This difference is partly

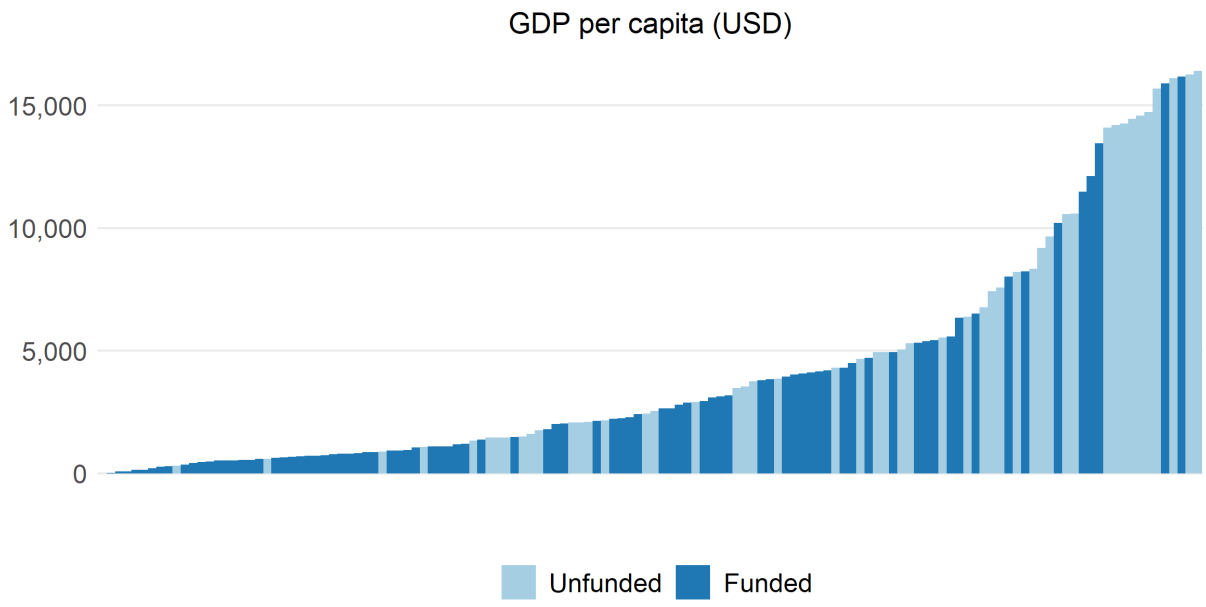
[7] We use yearly data primarily to scale higher frequency variables; for example, annual GDP is used in the denominator of IMF disbursements as percentage of GDP, and annual population data is used for COVID cases per million people.

[8] Further information on IMF lending can be found at https://www.imf.org/external/np/fin/tad/query.aspx and additional information on pandemic-related actions by the IMF can be accessed at https://www.imf.org/en/Topics/imf-and-covid19.

explained by the fact that PRGT countries entered the pandemic with lower fiscal space and more limited access to credit markets and therefore were more likely to request fast-disbursing financing from the IMF.

The cross-group heterogeneity also highlights important considerations for our analysis related to whether unfunded countries constitute a plausible comparison group. Lower levels of income are typically correlated with weaker governance and capacity to design and implement COVID support policies, which could lead to worse economic performance. On the other hand, weak enforcement of containment measures could lead to better economic performance at the expense of the public health outcomes. In the regressions, we attempt to overcome these issues by controlling for level of income and quality of governance. Relatedly, we opt to rely on the heterogeneity in the size of IMF lending, rather than making binary comparison between funded and unfunded countries to identify the economic effect of IMF lending. Even though we take these steps to better select appropriate controls, we observe a good amount of variation in income levels within the group of countries that received IMF financing, and countries that did not receive any funds at comparable income levels (Figure 1). The inclusion of very heterogeneous groups of LICs and EMEs that did not receive IMF financing also helps buttress our identification strategy.

Figure 1: GDP Per Capita Across Funded and Unfunded Countries, 2019 U.S. Dollars



Note: Funded countries refers to countries that received any type of IMF disbursement during 2020–21 and unfunded countries are those that did not receive any IMF disbursements. Countries in the sample are arranged in increasing order of GDP per capita along horizontal axis. See Annex I Table AI.1 for the full list of countries.

Turning to the outcome variables of interest, we use several high-frequency indicators which we take as proxies of economic activity. The first outcome variable measures individual mobility in retail, transit spaces, and other sectors, and is obtained from Google's Mobility Dataset (Google LLC, 2022). This data relies on mobile phone location data and considers the number of visits and length of stay at different locations, from which an index of the level of mobility is computed and made publicly available. The base for the index is the median value for the corresponding day of the week during the 5-week period from

January 3 to end-February 2020. The original data is available at daily frequency, which we average out into monthly observations. Our prior is that mobility is positively correlated with business transactions (e.g., shopping, work commuting) and hence with overall economic activity. These mobility indicators have been widely used to nowcast GDP and economic activity during the COVID-19 pandemic, with many studies showing their importance to tracking activity in real time during the pandemic (Sampi and Jooste, 2021; Haldane and Chowla, 2021; Gamtkitsulashvili and Plekhanov, 2021; Woloszko, 2020).

We use data on nighttime lights as the second non-conventional proxy for economic activity. This is sourced from the IMF's high-frequency COVID-19 Datahub, and the underlying information can be obtained from the Earth Observation Group's Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) dataset (Earth Observation Group, 2022; Elvidge, 2017). Monthly Cloud-free DNB Composite is aggregated up to the country level by summing up nighttime lights within administrative boundaries of each country. The resulting sum of lights measures the nighttime luminosity at the country level and monthly frequency. Following the literature, we associate stronger luminosity with more buoyant economic activity (see Beyer et al. 2022).

While these non-conventional proxies are not perfectly correlated with economic activity, several studies have estimated their elasticities with respect to GDP (Table 2). As we can see, these estimated ranges vary considerably across studies but still convey useful information about the actual behavior of the economy. Accordingly, in Section IV, we use the middle point of these ranges (0.2–0.8 for mobility and 0.3–0.7 for nighttime lights) to interpret the economic significance of our baseline findings.

Table 2: Elasticities of Economic Activity with respect to High-Frequency Proxies

Study	Mobility indicators	Nighttime lights
Gamtkitsulashvili and Plekhanov (2021)	53 emerging and advanced economies, elasticity with respect to value added: 0.2–0.4.	
Campos-Vazquez (2021)	Mexico: elasticity of point-of-sale expenditures with respect to mobility: 0.7–0.8.	
Beyer et al (2022)		EMEs and LICs, elasticity with respect to GDP: 0.6. All countries, elasticity with respect to GDP: 0.6–0.7.
Henderson et al (2012)		Global estimate: 0.3.
Roberts (2021)		Morocco: 0.262–0.295.

In addition, we construct a third indicator of economic activity, which in our view provides a more conventional and direct measure of GDP. We constructed this variable using information from seven different country-level indicators of economic activity—quarterly GDP, monthly coincident indicators of GDP, and monthly or quarterly measures of industrial production, real imports, real domestic credit, electricity consumption, and tourism arrivals. The underlying data was obtained from various data sources (primarily, countries' statistical agencies and central banks), and normalized to a 0–100 index to make

cross country comparisons possible. The final data is obtained by selecting the best available indicator in each country, in terms of economic relevance and/or frequency. Quarterly data was interpolated to monthly frequency using cubic spline interpolation. For most countries in our sample (over 60 percent), the variable selected is quarterly GDP (48 countries), followed by monthly coincident indicator of GDP (20), and monthly (or quarterly) industrial production (15). These three variables have been widely used as reliable indicators of economic activity. For the remaining countries, the variable selected relates to either real imports, real domestic credit, electricity consumption or tourist arrivals, depending on data availability. A detailed description of the indicator is provided in Annex I.[9]

Our conjecture is that IMF financing provided fiscal relief that enabled governments to implement larger response programs, thereby helping economic outcomes as proxied by the three variables described earlier. We therefore explore in regressions whether governments' fiscal response to COVID-19 increased with IMF financing. We collect fiscal spending data from IMF's "*Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic*" which records key fiscal measures that were taken or announced by governments. We use measure from both above-the-line (for example, COVID-related additional spending and foregone revenues from deferred taxes) and total liquidity support (including credit guarantees, equity injections, asset purchases, loans, and debt assumptions). Following the initial publication in June 2020, the database was updated to reflect cumulative measures approximately every 3-4 months. We combine six published vintages up to October 2021, resulting in 3-4 monthly frequency data series on fiscal spending for COVID response. Values between vintages are imputed as the last reported value.

Our regressions also control for important time-varying factors: severity of the pandemic, which we measure by the number of cumulative COVID-19 cases in per capita terms (i.e., per 1 million people)[10]; stringency of national lockdown measures through a stringency index that varies from 0 to 100, with greater values denoting more stringent measures; and other sources of financing—i.e., international reserves, and financing from the World Bank and other multilateral development banks (MDBs) that countries accessed during the pandemic. Data for the first two controls is sourced from Our World in Data. Data on international reserves comes from the IMF's International Financial Statistics (IFS) dataset.[11] We collected data on World Bank commitments for development finance and operations related to COVID-19, health and safety nets from the World Bank's Projects Website.[12] Data on commitments from other MDBs are obtained from the Center for Strategic and International Studies (CSIS) (Segal and

[9] It is important to note that we take what we think is the best available indicator for each country. We are not combining the available indicators for each country to construct a composite index of economic activity for that country. This is the case, for instance, of the coincident indicators of GDP (compiled and disseminated by country authorities) that we could find for 20 countries in our sample, and which is typically a composite of several high-frequency measures of economic performance such as industrial production, electricity consumption, imports volumes, etc.

[10] Cases may underrepresent the severity of the pandemic due to lack of testing, especially in the lowest income countries. We alternatively try using Covid deaths and find similar results.

[11] For local currency unions we make the following choices throughout. For all WAEMU members we assign the currency wide level of reserves, as IFS does not record reserves for each member country. For most CEMAC members we rely on imputed reserves as recorded in IFS up to 2020Q3. For ECCU members we use imputed reserves throughout 2020–21.

[12] See Projects & Operations | The World Bank.

Henderson, 2020).[13] We would have preferred to use information on disbursements from the World Bank and other MDBs but we could not find readily available information on pandemic-related disbursements. However, as we argue below for the IMF data, the difference between disbursements and commitments was not significant in the initial and most acute phase of the pandemic because the bulk of committed lending was disbursed.

Table 3 summarizes all variables used in this paper (also see Annex I, Table AI.2). We also report the country coverage for all outcome, fiscal, and control variables in Annex I, Table AI.3. Overall, coverage is quite high across most variables allowing us to analyze economic outcomes across a large set of low income and developing economies. Mobility indicators have the lowest country coverage with noticeably low percentage of PRGT-only countries reporting data. Nighttime lights have significantly better coverage for this set of countries and economic activity index is constructed for all countries in sample. The three outcome variables differ in the aspect of economic activity that they capture as well as coverage, and the three analyzed together offer a more robust understanding of the impact of IMF lending.

Table 3: Sample Summary Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Outcome Variables					
Mobility	Feb 2020=0	-12	25	-82	83
Nighttime lights	Million SOL[1]	2.33	8.45	0.002	136.75
Economic activity index	Dec 2016=100	103	36	0	355
Government Covid spending	Million USD	9,473	64,254	0	904,201
IMF Lending					
Disbursement	Million USD	245	783	0	8,102
Commitment	Million USD	254	902	0	7,970
Control Variables					
World Bank commitment	Million USD	184	463	0	4,200
MDB commitment	Million USD	313	751	0	5,504
Covid cumulative cases	Per million people	11,978	27,510	0	241,219
Stringency index	0–100	34	31	0	99
Reserves	Months of import	13	47	0	568

Notes: [1] Sum of lights (SOL) is the sum of radiance at pixel level within country boundaries.

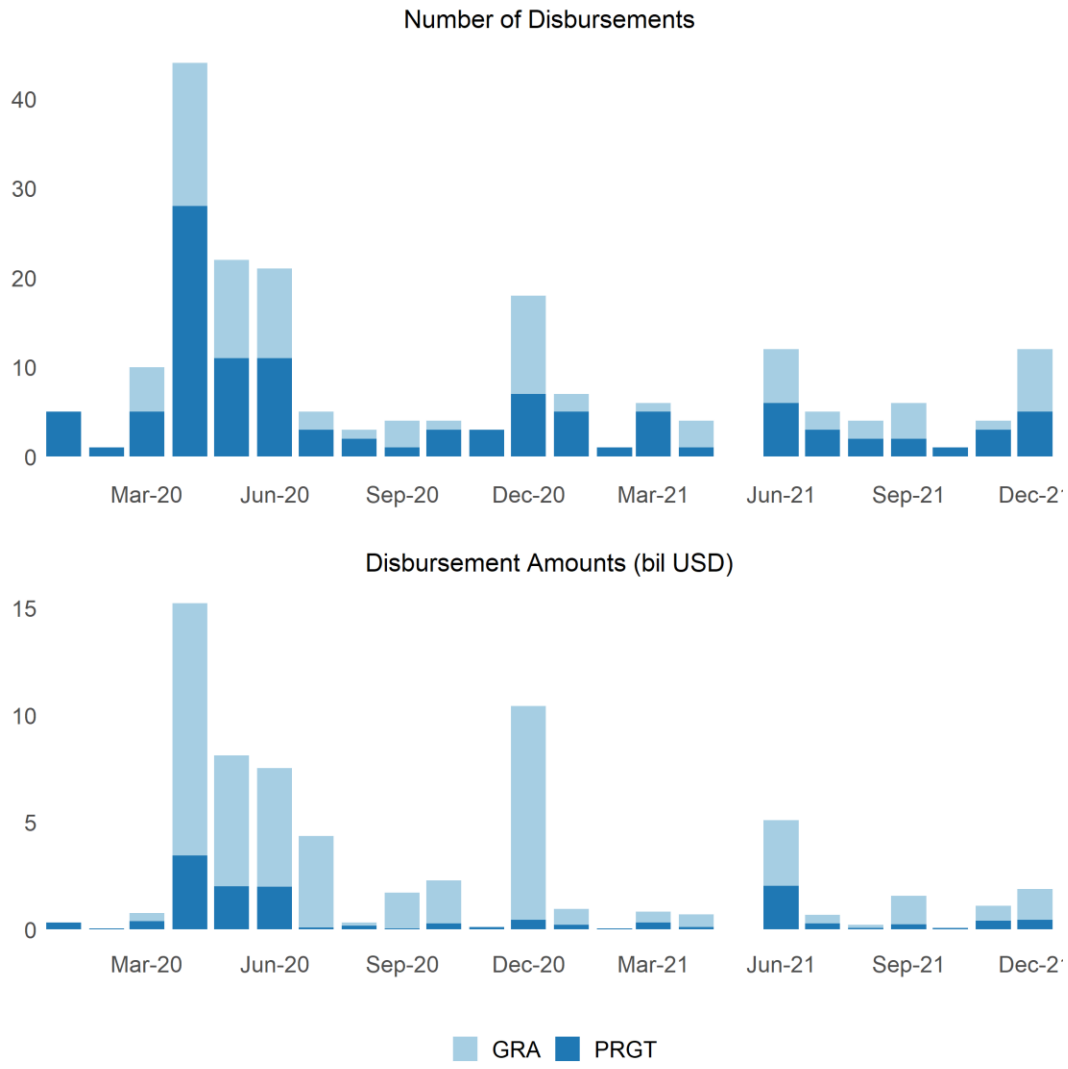
[13] MDBs covered by the data include African Development Bank, Asian Development Bank, Asian Infrastructure Investment Bank, European Bank for Reconstruction and Development, European Investment Bank, Inter-American Development Bank, Development Bank of Latin America, and New Development Bank. The data further includes select regional financing arrangements, including Arab Monetary Fund, Chiang Mai Initiative Multilateralization, Eurasian Fund for Stabilization and Development, European Stability Mechanism, and Latin American Reserve Fund. The database contains IFI funding approvals up to end of March 2021.

Descriptive Analysis

IMF Lending

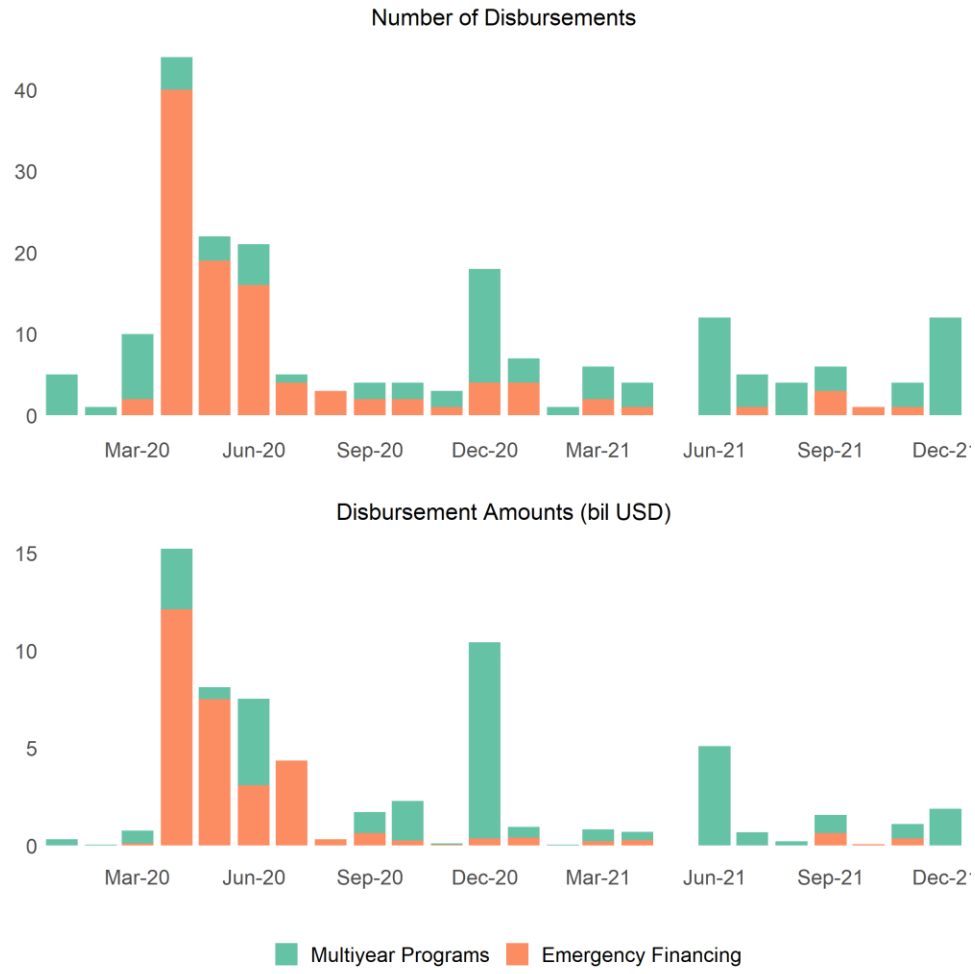
The IMF provided large amounts of emergency financing to countries in need at the outset of the pandemic. During the peak of IMF lending in April 2020, the PRGT made close to 28 disbursements to LICs and the GRA made 16 disbursements to EMEs (Figure 2). During 2020–2021, the IMF made 106 emergency loan disbursements to LICs and EMEs through the RCF/RFI instruments, and a further 96 disbursements under the arrangements for multiyear programs. Total disbursements amounted to approximately US$51.3 billion in 2020 and a further US$13.2 billion in 2021.

Figure 2: IMF Lending—Number of Disbursements (Top Panel) and Amounts Disbursed (Bottom Panel), 2020–2022



To accommodate this unprecedented amount of lending, over the course of the pandemic the IMF increased several times the access limits on the use of its resources thus providing more borrowing space to its members.[14] Although in the early months of the pandemic, IMF lending was carried out primarily through rapid disbursing emergency loans as mentioned above, over time there was a gradual shift towards financing support under multiyear IMF-supported programs (Figure 3).[15]

Figure 3: IMF Lending by Facility—Number of Disbursements (Top Panel) and Amount Disbursed (Bottom Panel), 2020–2022



[14] The increase in access limits under emergency financing instruments was temporary to meet the large demand for fast-disbursing pandemic-related lending. However, the increase in PRGT overall access limits (i.e., limits on the total borrowed amount) was made permanent to better help LICs cope with the fallout of the pandemic and support their economic recovery through multiyear programs. IMF (2021a) discusses the PRGT reforms that were approved in July 2021, which centered on a 45-percent permanent increase in PRGT overall access limits and removal of hard caps on access for the poorest LICs. IMF (2021b) provides an overview of the several changes in the IMF's access limits during the first two years of the pandemic.

[15] Some LICs and EMEs opted to receive emergency financing in two tranches, with the first typically in the early stages of the pandemic and the second a few months later. It is important to note that in normal circumstances a country cannot receive more than two RCF/RFI disbursements within a twelve-month period, however this constraint was temporarily lifted during the pandemic. The large spikes in amounts at end-2020 and mid-2021 mostly reflect large GRA purchases by a handful of EMEs.

While most eligible LICs and many EMEs received some form of IMF financial support, there was considerable variation across countries both in terms of size and financing modality (see Table 1 above). Some countries received emergency financing only, and several countries received both emergency financing and financing under IMF-supported programs, including via new programs or augmentation of existing programs. The large use of emergency financing facilities in the first phase of the pandemic reflected the urgency of the situation, but as the pandemic progressed countries expressed the need to address large balance of payments needs and implement reforms that could help pave the way for the economic recovery.[16] Given that such goals can be achieved more effectively through multiyear programs, over time there was a gradual exit from emergency support towards IMF-supported programs as mentioned above and as shown in Figure 3.

The observed heterogeneity in the nominal amounts of IMF financing received by each country mostly reflects country-specific circumstances, including the scale of balance of payments needs (which depends on several factors including the magnitude of the shock), the size of a country's quota at the IMF (e.g., access limits are defined as ratios to quota), the catalytic leverage of IMF financing (e.g., amount of financing that can be unlocked from other IFIs and development partners), and the country's available borrowing space under the IMF lending facilities as discussed above.

How did IMF lending compare to that from other IFIs? The IMF was one of the largest sources of external financing assistance during the pandemic, together with the World Bank and other MDBs (Figure 4). For 39 of 128 countries that received IFI financial support in 2020–2021, IMF support was the largest, i.e., greater than half of the combined financial support from major IFIs as we could measure in our data. Our regressions control for these other sources of financing to better identify the impact of IMF financing during the pandemic (see Section IV).[17] The timing of commitments approved by other IFIs (not shown here) also reveals that the IMF acted relatively quicker in the outset of the pandemic, as illustrated by the large amount of rapid-disbursing financing in the second quarter of 2020 (Figure 3).

Other potentially important sources of financing are not explicitly considered in our analysis. For instance, the 2021 general allocation of Special Drawing Rights by the IMF (2021 SDR allocation), equivalent to US$650 billion, provided much-needed liquidity to IMF members especially LICs and EMEs.[18] We do not consider this as a separate source of financing because it is partly captured in international reserves that we already control for. Furthermore, while the allocation was approved in August 2021, the period of operationalization (i.e., conversion of SDRs into usable reserve currencies) meant that the actual liquidity created mostly fell after our period of analysis. We also do not consider the debt service relief obtained by

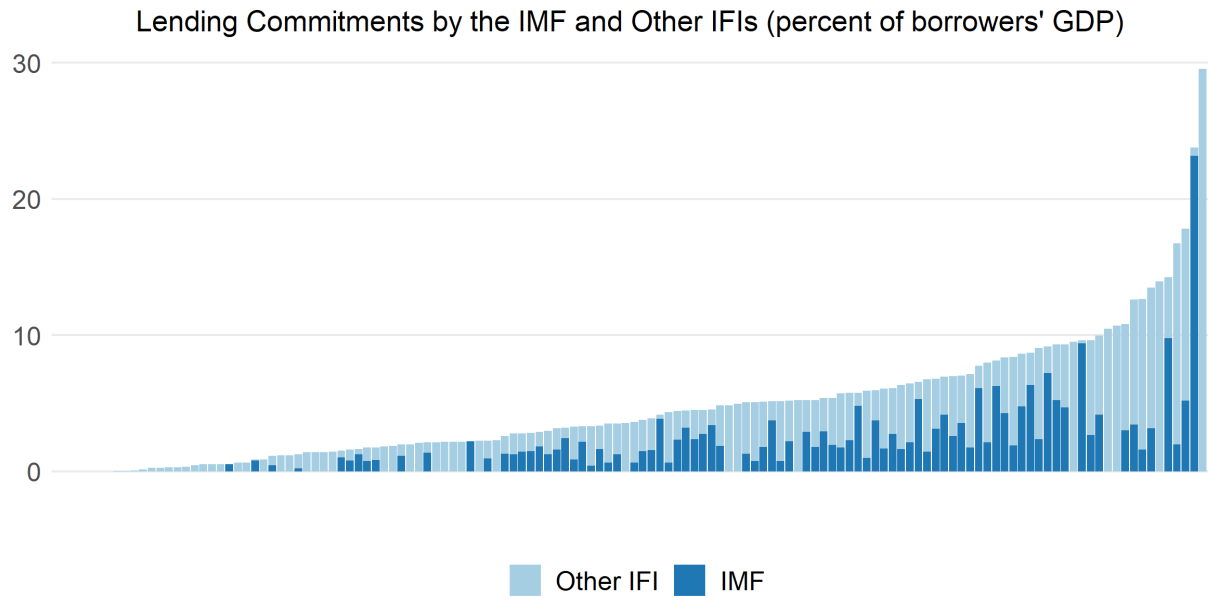
[16] Under the IMF lending policies, emergency financing can be provided to address urgent balance of payments needs where an upper credit tranche (UCT)-quality arrangement (i.e., a multiyear program typically entailing IMF financing, a reform package, and UCT conditionality) is either not necessary or not feasible.

[17] Data from IFIs are based on commitments. We could not find publicly available disbursement data from IFIs that was clearly related to the pandemic. The World Bank data was compiled by the authors using publicly available information on World Bank commitments on pandemic-related projects, programs, and budget support (Projects & Operations | The World Bank). Data on commitments by other IFIs was compiled by the Center for Strategic & International Studies (CSIS): CSIS IFI COVID-19 Response Tracker. As mentioned above, CSIS data only covers the period from January 2020 to March 2021. This shorter sample could in principle bias our estimates if the IMF-funded group was more prone to receive IFI funding than the unfunded group and/or more probable to receive IFI support after March 2021, both of which we find unlikely. In Section IV, we replace IMF disbursements with IMF commitments to check the robustness of our findings.

[18] See 2021 General SDR Allocation.

LICs and EMEs under the Debt Service Suspension Initiative (DSSI) and the IMF's Catastrophe Containment and Relief Trust (CCRT) because the eligible countries were not randomly selected (which could introduce some bias in our estimations) and because the amounts involved are substantially smaller compared to combined fresh financing provided by the IMF and other IFIs.[19]

Figure 4: Country-Level Pandemic-Related Lending by the IMF and Other IFIs, 2020–2021



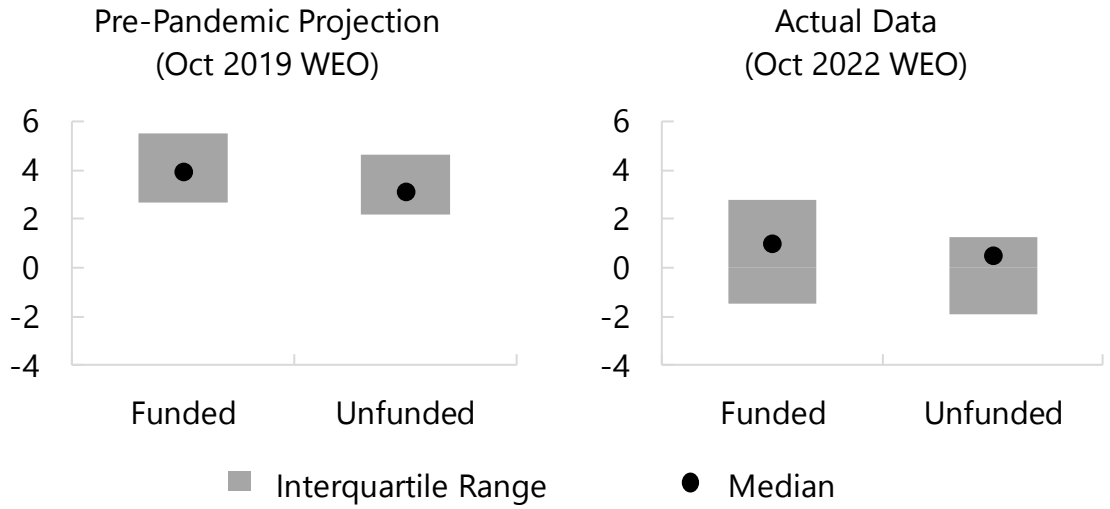
Note: Countries are ranked from lowest to highest in terms of total lending commitments by the IMF and Other IFIs.

High-Frequency Indicators

While GDP is the most traditional measure of economic activity, its availability at higher frequencies is limited, especially in the case of LICs. As a first pass, we looked at the annual GDP growth rates across IMF-funded and unfunded countries to check if we find significant differences across these two groups before and after the pandemic (Figure 5). The distribution of growth rates projected for the pandemic period was roughly similar across these two groups, i.e., similar medians and broadly symmetric interquartile ranges around the median (left panel). However, the distribution of actual growth rates for unfunded countries appears slightly skewed, suggesting that a somewhat larger fraction of these countries experienced lower growth than funded ones (right panel). In the next section, we test this observation more systematically using high frequency indicators of economic activity, which are first presented below.

[19] The DSSI suspended about US$13 billion in debt-service payments between May 2020 and December 2021 (see DSSI), whereas the CCRT provided about US$ 1 billion between April 2020 and April 2022 (see CCRT).

Figure 5: Annual GDP Growth, 2020–2021



Next, we conduct a simple descriptive analysis of each proxy of economic activity. Figure 6 plots time series of mobility indices for retail spaces and transit stations, respectively, for the IMF-funded and unfunded countries.[20] The figures show that both groups of countries experienced similar reductions in mobility at the onset of the pandemic, but on average, funded countries posted a faster and more robust recovery in mobility compared to unfunded countries. The results are similar for mobility at grocery stores and at workplaces (Annex II, Figure AII.1).

[20] While our regression analysis uses the variation across countries regarding the size of IMF disbursements, the analysis in this section makes a simple comparison between countries that received any IMF financing during 2020–21 (i.e., funded countries) and countries that did not receive any IMF financing (unfunded). See Table 1 for the sample sizes of funded and unfunded countries.

Figure 6: Mobility at Retail and Recreation Spaces and Transit Stations in Funded vs. Unfunded Countries (Percent change from baseline Jan–Feb 2020) [21]

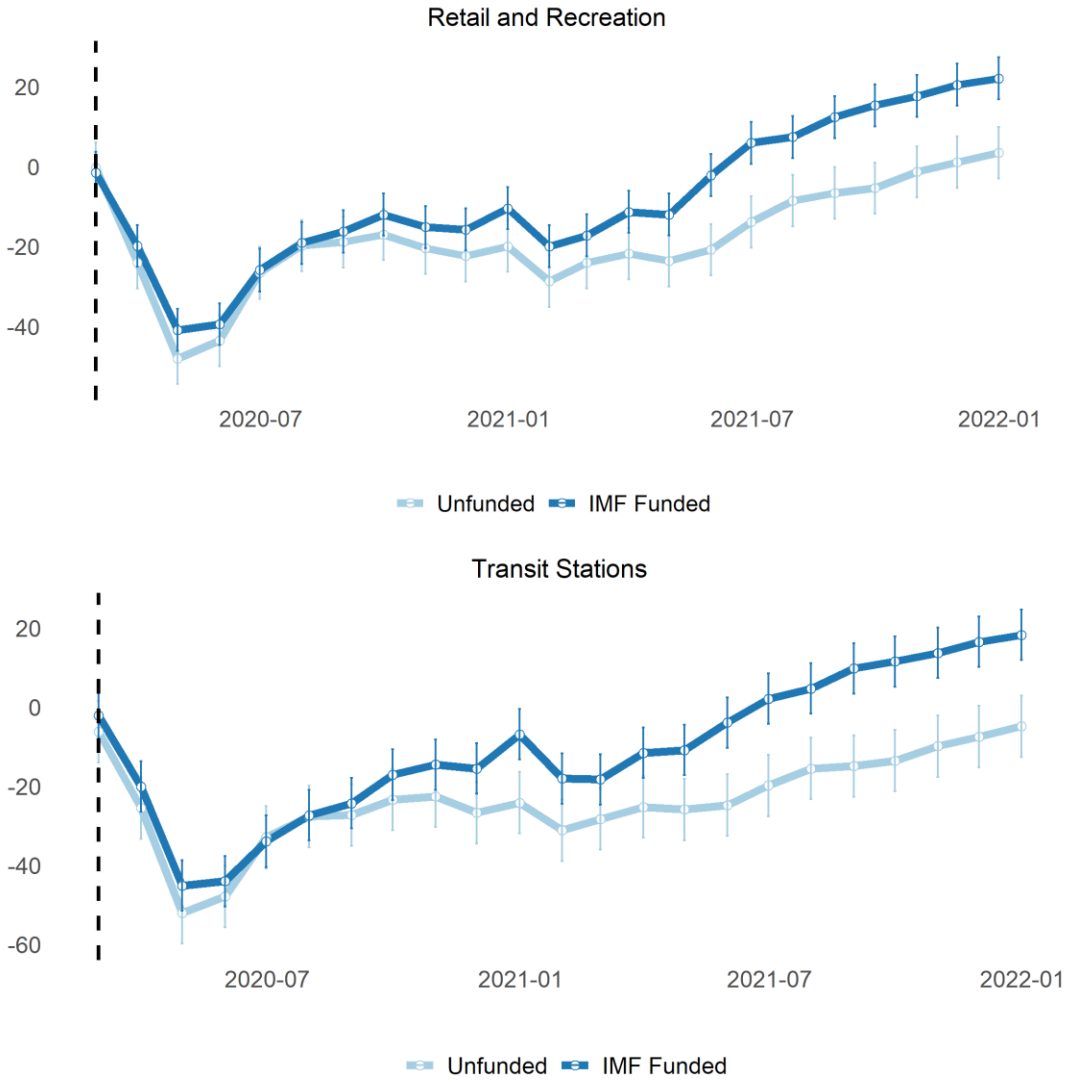
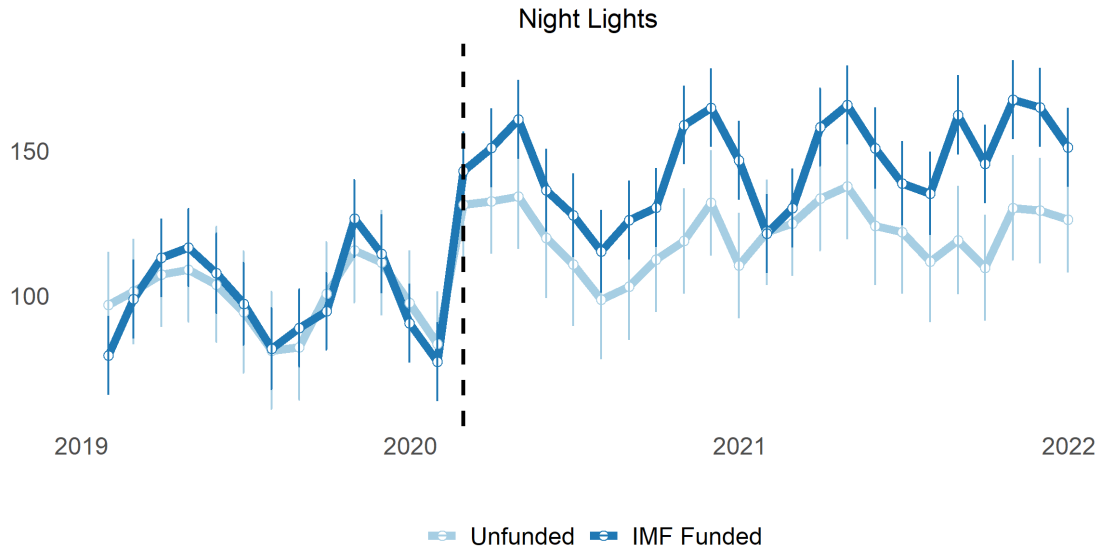


Figure 7 plots the nighttime lights data for the two groups of countries. We observe that nighttime lights behaved very similarly for the two groups in the months prior to the onset of the pandemic and the beginning of IMF's COVID-related emergency lending. The absence of different pre-trends lends some confidence to our identification strategy and choice of controls. However, it is still difficult to say whether funded countries would have recovered from a crisis similarly without funding. The chart also shows that during the pandemic, on average, funded countries experienced a greater increase in nighttime lights relative to unfunded countries.

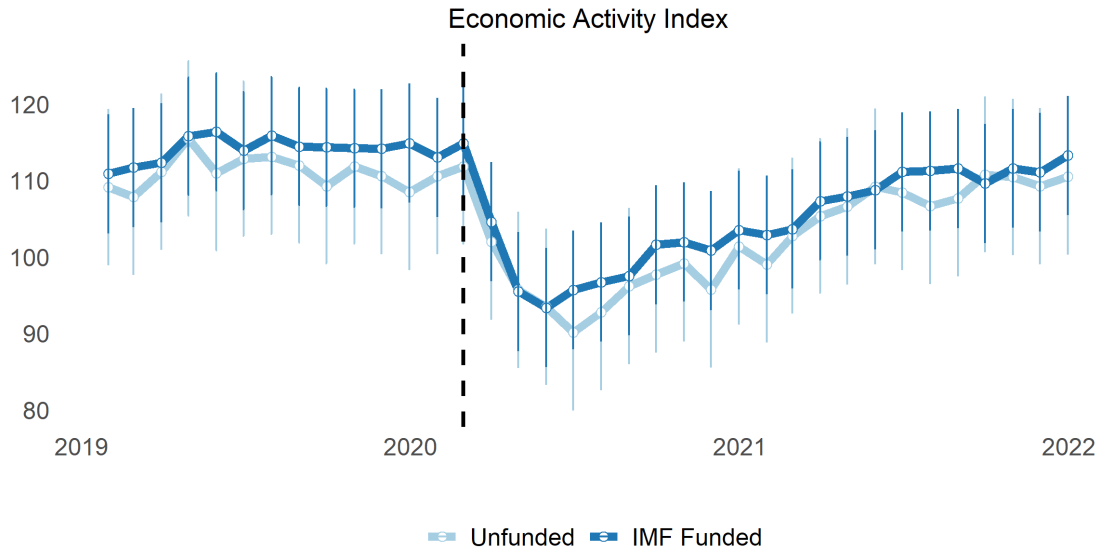
[21] For this and following similar figures, the error bars represent 95 percent confidence intervals for each group.

Figure 7: Nighttime Lights Index in Funded vs. Unfunded Countries, Jan 2019–Jan 2022 (Index, 2019=100)



Lastly, we plot our economic activity index for the two groups of countries in Figure 8. Unlike the two indirect measures of economic activity above, the index reveals only a very small difference across the two groups. The two groups of countries have similar pre-pandemic trends in the economic activity index, but the initial downturn is less severe for IMF-funded countries, which seem to start the recovery earlier than unfunded countries.

Figure 8: Economic Activity Index in Funded vs. Unfunded Countries, Jan 2019–Dec 2021 (Index, Dec 2016=100)



On balance, this exploratory analysis provides preliminary hints that IMF financing may be positively associated with high-frequency indicators of economic activity during the pandemic. However, we cannot infer any causal effect from these correlations. Furthermore, they do not control for cross-country differences in economic fundamentals and other factors, as well as for differences in the amounts and types of financing received from the IMF. Building on this analysis, in the next section, we estimate the regression model discussed above to test in a more systematic way whether IMF financing can be associated with positive economic outcomes.

Regression Results

Baseline Findings

Tables 4 to 6 present our baseline results across the three indicators of economic activity. Table 4 shows results based on mobility. The parameter of interest has the expected sign and is statistically significant across all the different specifications in the table. Larger IMF disbursements are found to be associated with higher rates of mobility during the pandemic across different spaces.

The estimated magnitudes suggest that β is also economically relevant. If we consider the specifications with the full set of controls (columns 2, 4, 6, 8), a 10-percent increase in IMF financing is associated with 0.07 to 0.15 percentage point change in the mobility relative to the baseline, depending on the space. We borrow from Table 2 the mid-point elasticity of economic activity with respect to mobility index, i.e., 0.5, to translate the magnitude of mobility increase to the magnitude of change in economic activity (value added or sales, per Table 2). In retail spaces, for example, a 10-percent increase in IMF financing translates to about 0.06 percent increase in economic activity.[22] Hence, an illustrative10-percent increase in IMF financing would be associated with about 0.06 percentage point higher economic activity in IMF-funded countries by the end of 2021, relative to unfunded countries. [23] We reiterate the point that the estimates are the average over the entire post-financing period; retail mobility index is 0.1 point higher every month (on average) after a 10-percent increase in IMF financing. The interpretation is analogous to that of binary 'post' effect in standard difference-in-differences setup with multiple periods.

As expected, the controls measuring the severity of the pandemic and stringency of lockdowns are negatively and significantly associated with mobility. Furthermore, in line with our priors, international reserves and access to other sources of international financing are positively associated with mobility but not statistically significant for the most part.

[22] A 10-percent increase in IMF financing leads to 0.11 unit increase in mobility index (column (2)). Applying the elasticity 0.5 gives about 0.06 increase in economic activity.

[23] A 10-percent increase in IMF financing is not particularly large for the median treated country in our sample. It would correspond roughly to 10 percent of quota (or about US$30 million) for the typical borrower. For reference, the RCF's per-disbursement limit—which, as noted in the previous section, was temporarily lifted in 2020–21—is much larger (25 percent of quota). On the other hand, the illustrative growth gains are probably overstated given that, for instance, it is unlikely that the extra resources (or the additional policy space created by the additional external financing) would affect all sectors of the economy in similar fashion.

Table 4: Impact of IMF Lending on Mobility

	Dependent variable: measured in percent change from baseline							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (log)	1.180***	1.069***	1.400***	1.370***	1.460***	1.445***	0.670***	0.713***
	(0.186)	(0.186)	(0.231)	(0.233)	(0.214)	(0.214)	(0.153)	(0.153)
Cumulative cases (log)	-3.133***	-3.170***	-2.015***	-1.869***	-3.151***	-2.873***	-1.660***	-1.851***
	(0.319)	(0.323)	(0.396)	(0.404)	(0.366)	(0.372)	(0.263)	(0.267)
Stringency Index	-0.487***	-0.489***	-0.433***	-0.438***	-0.531***	-0.538***	-0.290***	-0.284***
	(0.025)	(0.025)	(0.031)	(0.032)	(0.029)	(0.029)	(0.021)	(0.021)
Reserves (months of import)		0.439**		0.594**		0.924***		-0.781***
		(0.218)		(0.273)		(0.251)		(0.179)
WB, MDB funds (% of GDP)		1.410***		-0.116		-0.694*		0.094
		(0.310)		(0.388)		(0.357)		(0.255)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,657	1,657	1,657	1,657	1,657	1,657	1,655	1,655
R^2	0.831	0.834	0.818	0.819	0.821	0.822	0.715	0.718
Adjusted R^2	0.820	0.823	0.807	0.807	0.809	0.811	0.696	0.700
Residual Std. Error	11.038	10.942	13.702	13.690	12.659	12.606	9.039	8.989
Note:								*p<0.1, **p<0.05, ***p<0.01

The regressions based on nighttime lights yield largely similar results. The parameter of interest and the coefficient on the controls have the expected sign and are statistically significant, but the Stringency Index is shown not to be significantly associated with nighttime lights (Table 5). The estimates of β suggest that the impact of IMF lending on the economy also seems to be economically meaningful. For instance, if we measure nighttime lights in logs (columns 1 and 2), a 10-percent increase in IMF financing would be associated with almost 0.1 percent higher nighttime lights across IMF-funded countries on average over the period. Performing the same illustrative experiment as before and using the mid-point elasticity from Table 2 for nighttime lights (also 0.5), we find that a 10-percent increase in IMF financing would imply about 0.05 percentage point higher economic activity, similar to the value found for mobility.

Table 5: Impact of IMF Lending on Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.010***	0.008**	1.672***	1.339***
	(0.003)	(0.003)	(0.389)	(0.397)
Cumulative cases (log)	-0.029***	-0.026***	-3.270***	-2.944***
	(0.005)	(0.005)	(0.649)	(0.655)
Stringency Index	-0.0001	-0.0001	-0.008	0.001
	(0.001)	(0.001)	(0.063)	(0.063)
Reserves (months of import)		0.013***		1.531***
		(0.004)		(0.436)
WB, MDB funds (% of GDP)		0.011*		1.783**
		(0.006)		(0.750)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,619	2,619	2,619	2,619
R^2	0.975	0.975	0.716	0.718
Adjusted R^2	0.974	0.974	0.701	0.704
Residual Std. Error	0.279	0.278	34.587	34.458
Note:				*p<0.1, **p<0.05, ***p<0.01

Lastly, we estimate the impact of IMF lending on the economic activity index (Table 6). One advantage of this index is that it provides a direct elasticity between IMF financing and GDP growth. In line with previous results, the point estimates are positive and statistically significant.[24] However, the coefficients on the controls (COVID cases, Stringency Index and financing from other IFIs) do not have the expected sign. This may be because the expected correlations are confounded by an omitted variable. For example, countries with stronger institutions may report more cases and do better in economic recovery, even after conditioning on IMF financing. We report in Annex III, Table AIII.19 that controlling for income, governance, and political stability brings the estimates for the coefficients on COVID cases and Stringency Index to the expected sign, suggesting that these controls go some way in helping to mitigate the omitted variable. Generally, the same issue matters to varying degrees depending on the outcome variable. For example, a larger number of COVID cases directly limit people from going outside, implying

[24] We try clustering standard errors at the country level and report results in Annex III, Tables AIII.10–12. We turn to this issue again in the robustness sections below.

a strong negative correlation between cases and mobility measure that comes through any confounding effects.

In terms of economic significance, if we consider the log specifications in columns 3 and 4, a 10-percent increase in IMF lending would be associated with a 0.15–0.2 percent point increase in economic activity. Considering that our index primarily reflects the behavior of actual GDP and industrial production, this estimate can be interpreted as an equivalent increase in GDP.

Table 6: Impact of IMF Lending on Economic Activity Index

	Dependent variable:			
	Economic Activity (Index)		Economic Activity (log)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.742***	1.013***	0.015***	0.019***
	(0.161)	(0.161)	(0.005)	(0.005)
Cumulative cases (log)	0.379	0.191	0.037***	0.033***
	(0.252)	(0.251)	(0.007)	(0.007)
Stringency Index	0.035	0.033	0.003***	0.003***
	(0.024)	(0.024)	(0.001)	(0.001)
Reserves (months of import)		0.087		-0.004
		(0.195)		(0.006)
WB, MDB funds (percent of GDP)		-2.787***		-0.042***
		(0.259)		(0.008)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	3,130	3,130	3,130	3,130
R^2	0.803	0.811	0.656	0.659
Adjusted R^2	0.794	0.802	0.639	0.643
Residual Std. Error	15.179	14.892	0.437	0.435
Note:				*p<0.1, **p<0.05, ***p<0.01

These back-of-envelope calculations for mobility, nighttime lights, and economic activity index suggest that the positive effect of IMF financing on the real economy is relatively modest but non-trivial, with magnitude in the ballpark of 0.1–0.2 percent of GDP per 10 percent increase in IMF funding. To further put this number into perspective, we compare the outcomes for the median and top quartile countries. Over the 2020-21 period, the median funded country received US$277 million in lending. The top quartile funded country received US$639 million, or over twice as much as the median funded country. Our estimates suggest that increasing financing of the median funded country to the level of top quartile

country would imply a higher GDP by almost 3 percentage points over the two-year period, a very substantial effect.

These findings are significant in the baseline and across the robustness tests, but our findings are based over a unique time period, where the outbreak of the global health pandemic was associated with an unusually sharp initial downturn – therefore we caution the broader applicability of these back-of-envelope calculations. While traditional IMF programs in times of economic crises typically lead to improved external balances, tighter fiscal policy and potentially lower growth in the short-run, our results suggest that higher economic activity in the short-run should be considered in the specific context of the COVID-19 pandemic. Furthermore, we interpret our findings as not necessarily boosting economic growth, but rather supporting economic activity in funded countries – i.e., mitigating the economic downturn relative to unfunded countries – in the face of a health shock that required social distancing and work closures for non-economic reasons. Lastly, IMF financing in this crisis period was mostly related to government budget support (see below), which allowed to increase government expenditures to assist households and firms. As we would expect, this countercyclical fiscal policy would help mitigate the economic downturn immediately after the onset of the pandemic relative to the situation without Fund support. Next, we provide further nuance to our baseline findings by analyzing several dimensions of cross-country heterogeneity.

Cross-Country Heterogeneity

While our baseline results suggest a positive effect of IMF lending on borrower's economic activity during the pandemic, we also investigate whether these effects vary across country groups. In this section, we analyze whether IMF lending has a differentiated impact depending on income level, capacity to implement government policies, and institutional quality.[25]

When activity is measured by mobility (columns 1–3 of Table 7), we find that IMF financing has a positive effect in countries across all income groups (low-, middle- and high-income). A similar pattern is also observed when we group countries by institutional quality. On the other hand, the marginal effect of IMF financing is larger for countries that score lower in terms of rule of law. Turning to nighttime lights (columns 4–6 of Table 7), we continue to find the largest marginal effect of IMF financing on economic activity in LICs and in countries with lower scores of government effectiveness and the rule of law. However, the statistical significance vanishes for the other groups of countries. These findings are not surprising given the strong correlation between institutions and level of economic development. However, as discussed in the previous sections, most LICs had reduced policy and financing spaces to respond to the pandemic compared with higher-income countries. Even the better off LICs (e.g., "frontier LICs" and Blenders) were shut down from international capital markets during the pandemic. Hence, prompt disbursements by the IMF possibly helped relax financing constraints, both directly and by catalyzing

[25] We use real GDP per capita as of 2019 to group countries by income level. We measure implementation capacity and institutional quality by the Worldwide Governance Indicators (WGI)' *Government Effectiveness* and *Rule of Law*, respectively (Kaufmann et al 2011). We order countries by each measure and define the bottom third countries as "low", middle third as "mid", and top third as "high" group. Therefore, the grouping is defined relative to countries within our sample and does not reflect absolute levels of income or governance.

support from the official sector for the poorest LICs, while temporarily replacing some of the market financing in frontier LICs.

Table 7: Heterogeneity: Mobility and Nighttime Lights

	Dependent variable: in percent change from baseline					
	Retail Mobility			Night Lights		
	(1)	(2)	(3)	(4)	(5)	(6)
IMF Disbursement (log) X Income: Low	1.133***			3.452***		
	(0.314)			(0.545)		
IMF Disbursement (log) X Income: Mid	0.798**			-0.573		
	(0.322)			(0.605)		
IMF Disbursement (log) X Income: High	1.109***			-0.338		
	(0.338)			(0.775)		
IMF Disbursement (log) X Gov Effective: Low		0.979***			1.614**	
		(0.350)			(0.684)	
IMF Disbursement (log) X Gov Effective: Mid		1.228***			1.024*	
		(0.327)			(0.553)	
IMF Disbursement (log) X Gov Effective: High		0.940***			0.124	
		(0.303)			(0.714)	
IMF Disbursement (log) X Rule of Law: Low			1.198***			3.499***
			(0.298)			(0.515)
IMF Disbursement (log) X Rule of Law: Mid			1.405***			0.407
			(0.285)			(0.552)
IMF Disbursement (log) X Rule of Law: High			0.435			-0.233
			(0.386)			(0.767)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE X Income	Yes	No	No	Yes	No	No
Month FE X Gov Effective	No	Yes	No	No	Yes	No
Month FE X Rule of Law	No	No	Yes	No	No	Yes
Observations	1,657	1,657	1,657	2,619	2,619	2,619
R^2	0.786	0.786	0.787	0.698	0.699	0.693
Adjusted R^2	0.775	0.775	0.775	0.685	0.686	0.680
Residual Std. Error	12.350	12.357	12.345	35.509	35.471	35.783

Note: *p<0.1, **p<0.05, ***p<0.01

Table 8: Heterogeneity: Economic Activity Index

	Dependent variable:		
	Economic Activity Index (Dec 2016 = 100)		
	(1)	(2)	(3)
IMF Disbursement (log) x Income: Low	0.853***		
	(0.225)		
IMF Disbursement (log) x Income: Mid	0.543**		
	(0.246)		
IMF Disbursement (log) x Income: High	-0.613**		
	(0.305)		
IMF Disbursement (log) x Gov Effective: Low		0.777***	
		(0.282)	
IMF Disbursement (log) x Gov Effective: Mid		0.344	
		(0.227)	
IMF Disbursement (log) x Gov Effective: High		0.558**	
		(0.280)	
IMF Disbursement (log) x Rule of Law: Low			1.274***
			(0.208)
IMF Disbursement (log) x Rule of Law: Mid			0.267
			(0.220)
IMF Disbursement (log) x Rule of Law: High			-0.427
			(0.297)
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Month FE X Income	Yes	No	No
Month FE X Gov Effective	No	Yes	No
Month FE X Rule of Law	No	No	Yes
Observations	3,130	3,130	3,130
R^2	0.796	0.794	0.800
Adjusted R^2	0.788	0.786	0.792
Residual Std. Error	15.381	15.461	15.237

Note: *p< 0.1, **p<0.05, ***p<0.01

The findings based on the economic activity index are broadly consistent with those in Table 7.IMF financing seems to exert a proportionally larger impact in countries with lower income and weaker governmental capacity and institutions (Table 8). To illustrate, compared to middle-income countries, the effect of IMF financing in low-income countries is about 60 percent larger than in middle-income countries (Table 8, column 1). Similarly, when controlling for governance and rule of law, the effect of IMF financing is the greatest and sometimes the only significant in the lowest third group.

Next, we investigate whether the type of IMF lending matters for our baseline findings. To this end we disaggregate IMF disbursements by modality: PRGT concessional borrowing by LICs, and GRA purchases by the other IMF members in our sample. We find that additional PRGT financing is significantly and positively associated with higher rates of mobility, nighttime lights, and economic activity. The effect on nighttime lights is greater for this subset of countries than the marginal effect of additional GRA financing to the non-LIC group of countries, while the effect on mobility and economic activity index are similar (Table 9).

Our conjecture remains that PRGT financing has the potential for larger marginal value to LICs given their more constrained policy space and access to international credit markets. However, it is also conceivable that in higher income countries that have better institutions to design and implement crisis response may be able to deploy funds more effectively. The findings of this section, which reflect cross-country heterogeneity along various dimensions (Tables 7–9) suggest that on balance, financially constrained countries could have been benefited proportionally more from IMF lending.

Table 9: Heterogeneity: IMF Concessional vs. Non-concessional Lending

	Dependent variable:[1]		
	Retail Mobility	Night Lights	Economic Activity
	(1)	(2)	(3)
IMF Disbursement (log) x PRGT	1.103***	2.286***	0.529**
	(0.358)	(0.631)	(0.266)
IMF Disbursement (log) x GRA	1.100***	0.059	0.514**
	(0.233)	(0.483)	(0.199)
Controls	Yes	Yes	Yes
Country Fixed Effects (FE)	Yes	Yes	Yes
Month FE x PRGT or GRA	Yes	Yes	Yes
Observations	1,657	2,619	3,130
R^2	0.785	0.706	0.794
Adjusted R^2	0.774	0.694	0.786
Residual Std. Error	12.384	35.010	15.460

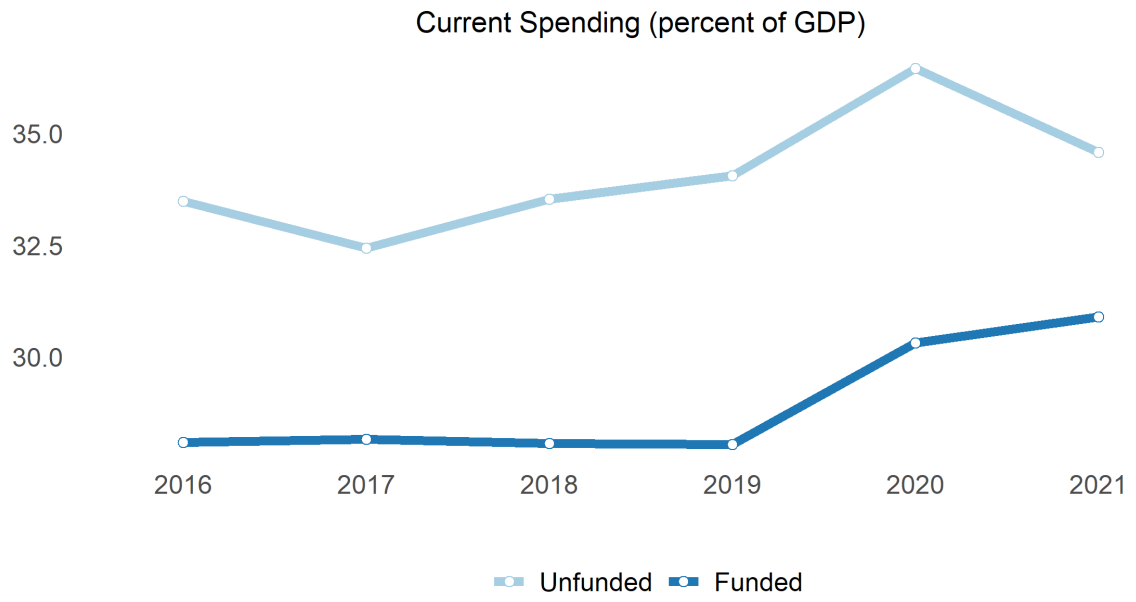
Note: *p<0.1, **p<0.05, ***p<0.01

[1] *Mobility is deviation from baseline levels (Jan-Feb 2020).*

A Possible Fiscal Transmission Channel

Traditionally, IMF lending has focused on strengthening a country's external buffers, particularly the level of international reserves adequacy. However, during the pandemic a significant fraction of IMF disbursements was channeled for budget support, especially in the case of LICs. For instance, a survey of published IMF staff reports on emergency financing requests by LICs between March 2020 and June 2022 reveals that about four-fifths of those requests intended to use part or all IMF disbursements to support the government budget. Therefore, one of the main channels through which IMF financing could have impacted economic activity during the pandemic was through increasing the fiscal resources available to implement measures to stabilize the economy, prepare health systems, and cushion the impact of national lockdowns on workers and firms. Furthermore, Aizenman et al (2022) find that higher government spending across 71 countries during COVID-19 is associated with higher commercial bank lending, thereby further supporting economic activity. Figure 9 provides some credence to the hypothesis that IMF funding may have helped bolster the fiscal response to the pandemic. As the figure shows, funded countries were able to sustain higher levels of spending in 2020–2021 relative to 2019 levels, whereas unfunded countries seem to have normalized fiscal spending already in 2021.

Figure 9: Annual Current Government Spending for Funded and Unfunded Countries



Note: Annual spending data is from the IMF's World Economic Outlook Database.

We further test this conjecture by estimating the impact of IMF financing on government expenditure, while keeping the standard set of control variables in the regression. We find that when we account for group-specific time trends, IMF financing is positively and significantly associated with government expenditure. Specifically, if we interact time trends with income groups and institutional quality, which would help capture the differentiated impact on LICs, we find that a 10 percent increase in IMF financing (about US$ 30 million for the IMF typical borrower during the pandemic) would be associated with about a 0.4 percent increase in government COVID-related spending or about 0.2 percentage point of GDP for

the median country in our sample (columns 1–4 of Table 10). In columns 5–8 of Table 10, we also analyze the combined value of COVID spending and COVID liquidity support measures and find no significant effect of IMF financing. Together, the results suggest that IMF financing helped sustain government expenditures, but the measures were confined to direct spending rather than liquidity support measures. These results could possibly also reflect the indirect impact of IMF financing in catalyzing financing from other large multilateral donors, as mentioned above, and/or in supporting domestic credit as argued by Aizenman et al (2022). [26]

Table 10: Government COVID-Related Fiscal Spending

	Dependent variable:							
	Covid Spending (log)				Covid Response Total (log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (log)	0.023	0.040*	0.013	0.042**	-0.005	0.013	-0.014	0.019
	(0.022)	(0.021)	(0.021)	(0.021)	(0.023)	(0.022)	(0.022)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE X Income	Yes	No	No	No	Yes	No	No	No
Month FE X Gov Effective	No	Yes	No	No	No	Yes	No	No
Month FE X Rule of Law	No	No	Yes	No	No	No	Yes	No
Month FE X PRGT or GRA	No	No	No	Yes	No	No	No	Yes
Observations	3,070	3,070	3,070	3,070	3,070	3,070	3,070	3,070
R^2	0.779	0.781	0.779	0.781	0.781	0.783	0.781	0.784
Adjusted R^2	0.770	0.773	0.770	0.773	0.772	0.775	0.772	0.775
Residual Std. Error	1.981	1.971	1.982	1.971	2.062	2.050	2.062	2.047
Note:								*p<0.1, **p<0.05, ***p<0.01

Robustness Analysis

In this section we discuss alternative specifications to check the robustness of our baseline findings.

As discussed above in the context of the baseline specification, the staggered timing of IMF disbursements could bias the estimated coefficient on the treatment variable. To address this problem, we redefine treatment event to include disbursements made in April–June of 2020 and drop countries that receive disbursements after June 2020. This period covers the significant disbursements made by the IMF during the first "wave" of the pandemic (see Section III). The main difference with respect to the baseline treatment is that countries that received additional support in later stages of the pandemic are excluded from the analysis. This approach yields similar results as the baseline. IMF lending continues to

[26] The catalytic role of IMF financing during the pandemic is an interesting issue that we leave for future research.

have a significant impact on all measures of economic activity (Annex III, Tables AIII.2–III.4). We also note that the magnitude of the estimated coefficient is comparable to that in the baseline. We therefore conclude that our baseline findings are robust to the staggered timing of IMF disbursements.

Second, we explore whether scale effects may be affecting our baseline estimates. To this end, we change our baseline model using disbursement amounts as a percent of GDP instead of in levels, while keeping all other variables as measured in the baseline. We find that IMF lending remains significantly and positively correlated with all outcome variables (Annex III, Tables AIII.5–III.7). In addition, with a view to ensure that the scaling variable is exogenous, we re-estimate our baseline model using disbursement amounts as a percent of IMF quota. In most specifications, the effect of IMF lending remains positive and statistically significant (Annex III, Tables AIII.8–10). Hence, our findings do not seem to be a by-product of measurement effects.

Third, we substitute IMF disbursements with new commitments as the treatment variable. For emergency financing facilities, which were heavily used in the first phase of the pandemic, the two are equivalent. Generally, multiple disbursements are made under multiyear programs, typically dispersed about three-to-six months apart. Therefore, the actual amount disbursed in a given period may be less than the total committed amount in the case of countries that have initiated but not yet completed a program in 2020–21, while it may exceed commitments in the case of countries that had initiated programs prior to pandemic. We find that our baseline results for all outcome variables are robust to this specification (Annex III, Tables AIII.11–III.13).

As mentioned above, we also tested whether our baseline results are robust to clustered standard errors at the country level. We find that standard errors are generally larger and reduce the statistical significance of the coefficients on the nighttime lights index and economic activity index (when measured in logs). However, the coefficients on the remaining outcome variables (log of nighttime lights, level of economic activity index, and all measures of mobility) remain positive and statistically significant (Annex III, Tables AIII.14–16).

Fifth, we estimate the effect of emergency financing only, i.e., excluding all disbursements under Fund-programs. Emergency financing could be unlocked more easily and quickly given the urgent need to provide COVID support and absence of multi-period monitoring and conditionality that typically feature in traditional IMF programs. Therefore, this approach helps isolate the effect of immediate liquidity provision. The impact of IMF emergency financing is found to remain positive and significant across all outcome variables (Annex III, Tables AIII.17–19).

Conclusion

In this paper we estimated the impact of IMF COVID-related financing on economic performance using a comprehensive sample that covers the IMF’s various lending facilities, several high-frequency proxies of economic activity, and a wide range of LICs and emerging market economies. We construct a novel database that merges monthly IMF disbursement data with monthly conventional and non-conventional proxies of economic activity, measures of the severity of the pandemic, and stringency of lockdowns. Our

descriptive analysis provides anecdotal evidence suggesting a positive role of IMF financing in the countries that received IMF funding compared to countries that did not receive any IMF financing during the pandemic. This analysis also helped motivate our regression analysis, in which funded and unfunded countries have similar pre-pandemic trends in the outcome variables of interest but differ with respect to access to IMF financing during the pandemic. If IMF lending had played no role during the pandemic, we would expect that the post-pandemic trends across these two country groups would remain broadly similar.

However, our baseline findings suggest that IMF financing had a significant and positive impact on key proxies of economic activity, i.e., four indicators of mobility, measures of nighttime luminosity, and traditional higher-frequency measures of economic activity. Back-of-envelope calculations suggest that a 10-percent increase in IMF financing would be associated with up to 0.2 percentage point higher levels of economic activity in IMF-funded countries relative to unfunded ones.

We document that our baseline results hold under several alternative specifications. IMF financing continues to have a positive and significant impact on economic performance when we control for different measures of country group heterogeneity (income, policy implementation capacity, institutions) and types of IMF lending facilities (concessional vs. non-concessional, and emergency vs. program). Furthermore, the data seems to suggest that IMF financing may have eased fiscal financing constraints during the first two years of the pandemic. We also show that our baseline findings survive a host of robustness tests, including alternative timing of IMF disbursements, differences in lending modalities (disbursements vs. commitments), differences in type of financing (emergency financing vs. all types of financing), and scaling our treatment variable by country size which we measure by GDP and IMF quota. This gives us confidence that our results are not an artifact of the data or econometric specifications used.

The evidence presented in this paper sheds light on the debate about the role of IMF interventions. The pandemic provides a useful context that allows to better identify and test the economic impact of IMF financing. Our findings suggest that IMF financing, including in the form of direct budget support, can help countries navigate and manage acute crises. Assessing whether these interventions are efficient or at the optimal scale are interesting issues but go beyond the scope of our research. We also leave for future research the question of whether the short-term effects that we estimated in this paper can be identified over longer-horizons, including in the context of multiyear programs.

Finally, our findings suggest that lower-income countries may have experienced a larger marginal benefit from IMF financing than higher-income IMF members. Although the IMF's concessional financing trust (the PRGT) has a relatively small scale compared to other sources of concessional financing (e.g., IDA, official bilateral grants),[27] our results suggest that the support provided by the PRGT during the pandemic probably helped ease the economic costs of the pandemic in the poorest countries.

[27] To put the PRGT into perspective, pre-pandemic it was funded to support a self-sustaining lending envelope of SDR 1¼ billion (about US$ 1.7 billion) per year. Although this was increased in 2021 to SDR 1.65 billion (about US$2.4 billion) per year (see IMF, 2021a), it remains a fraction of IDA's annual commitments, for instance.

Annex I. Data

Table AI.1:Sample of Countries

Country	Income category	IMF loan	Country	Income category	IMF loan
Afghanistan	LIC	Yes	Kosovo	EME	Yes
Bangladesh	LIC	Yes	Maldives	EME	Yes
Benin	LIC	Yes	Mongolia	EME	Yes
Burkina Faso	LIC	Yes	Montenegro	EME	Yes
Burundi	LIC	Yes	Morocco	EME	Yes
Cameroon	LIC	Yes	Namibia	EME	Yes
Central African Republic	LIC	Yes	North Macedonia	EME	Yes
Chad	LIC	Yes	Pakistan	EME	Yes
Comoros	LIC	Yes	Panama	EME	Yes
Congo, Democratic Republic of	LIC	Yes	Samoa	EME	Yes
Cote d'Ivoire	LIC	Yes	Seychelles	EME	Yes
Djibouti	LIC	Yes	South Africa	EME	Yes
Ethiopia	LIC	Yes	St. Lucia	EME	Yes
Gambia, The	LIC	Yes	St. Vincent and Grenadines	EME	Yes
Ghana	LIC	Yes	Suriname	EME	Yes
Guinea	LIC	Yes	Tonga	EME	Yes
Guinea-Bissau	LIC	Yes	Tunisia	EME	Yes
Haiti	LIC	Yes	Ukraine	EME	Yes
Honduras	LIC	Yes	Bhutan	LIC	No
Kenya	LIC	Yes	Cambodia	LIC	No
Kyrgyz Republic	LIC	Yes	Congo, Republic of	LIC	No
Lesotho	LIC	Yes	Kiribati	LIC	No
Libera	LIC	Yes	Lao People's Democratic Republic	LIC	No
Madagascar	LIC	Yes	Timor-Leste	LIC	No
Malawi	LIC	Yes	Vietnam	LIC	No
Mali	LIC	Yes	Zambia	LIC	No
Mauritania	LIC	Yes	Algeria	EME	No
Moldova, Republic of	LIC	Yes	Antigua and Barbuda	EME	No
Mozambique	LIC	Yes	Argentina	EME	No
Myanmar	LIC	Yes	Azerbaijan	EME	No
Nepal	LIC	Yes	Belize	EME	No
Nicaragua	LIC	Yes	Botswana	EME	No
Niger	LIC	Yes	Brazil	EME	No
Nigeria	LIC	Yes	Bulgaria	EME	No
Papua New Guinea	LIC	Yes	Chile	EME	No
Rwanda	LIC	Yes	China	EME	No
Sao Tome & Principe	LIC	Yes	Croatia	EME	No
Senegal	LIC	Yes	Fiji	EME	No
Sierra Leone	LIC	Yes	Guyana	EME	No
Solomon Islands	LIC	Yes	Hungary	EME	No
South Sudan	LIC	Yes	India	EME	No
Tajikistan, Republic of	LIC	Yes	Indonesia	EME	No
Tanzania	LIC	Yes	Kazakhstan	EME	No
Togo	LIC	Yes	Malaysia	EME	No
Uganda	LIC	Yes	Marshall Islands	EME	No

Country	Income category	IMF loan	Country	Income category	IMF loan
Uzbekistan, Republic of	LIC	Yes	Mauritius	EME	No
Albania	EME	Yes	Mexico	EME	No
Angola	EME	Yes	Micronesia, Federated States of	EME	No
Armenia	EME	Yes	Nauru	EME	No
Barbados	EME	Yes	Oman	EME	No
Bolivia	EME	Yes	Palau	EME	No
Bosnia and Herzegovina	EME	Yes	Paraguay	EME	No
Cabo Verde	EME	Yes	Peru	EME	No
Colombia	EME	Yes	Philippines	EME	No
Costa Rica	EME	Yes	Poland	EME	No
Dominica	EME	Yes	Romania	EME	No
Dominican Republic	EME	Yes	Russian Federation	EME	No
Ecuador	EME	Yes	Serbia	EME	No
Egypt, Arab Republic	EME	Yes	Sri Lanka	EME	No
El Salvador	EME	Yes	St. Kitts and Nevis	EME	No
Equatorial Guinea	EME	Yes	Thailand	EME	No
Eswatini	EME	Yes	Trinidad and Tobago	EME	No
Gabon	EME	Yes	Turkey	EME	No
Georgia	EME	Yes	Turkmenistan	EME	No
Grenada	EME	Yes	Tuvalu	EME	No
Jamaica	EME	Yes	Uruguay	EME	No
Jordan	EME	Yes	Vanuatu	EME	No

Table AI.2: Variable Description

Variable	Description	Unit
Outcome variables		
Mobility	We focus on four location categories: retail and recreation, grocery and pharmacy, transit stations, and workplaces.	Percent change from baseline (Jan–Feb 2020)
Nighttime lights	Sum of nighttime lights within national borders. Cloud coverage and stray light adjusted.	
Economic Activity Index	This is measured by seven high-frequency indicators of economic activity, including GDP, coincident indicators of GDP, and industrial production (see below)	Index, Dec 2016=100
Government Covid-19 Spending	Sum of additional government fiscal spending and under-the line liquidity support for Covid-19	Millions of US$
Treatment variables		
IMF Disbursement	Cumulative IMF disbursements made in 2020-21.	Millions of US$
IMF Commitment	Cumulative IMF commitments on new arrangements made in 2020-21.	Millions of US$
Control variables		
COVID-19 cases	Cumulative Covid-19 confirmed cases	Case per million population
Stringency index	Stringency of lockdown-style containment measures	Index, 0–100
Reserves	Foreign currency reserves	Months of import
MDB commitments	Cumulative World Bank and other IFI commitments for Covid support	Millions of USS

Table AI.3: Number of Countries with Available Data

Variable	PRGT only	Blender	GRA only
Mobility	17	13	53
Nighttime lights	32	17	55
Government COVID-19 Spending	45	18	69
COVID-19 Cases	44	19	68
COVID-19 Deaths	42	19	68
Stringency Index	36	18	62
Reserves	40	18	66
All in-sample	45	19	70

Monthly Indicator of Economic Activity

As we discussed in Sections I and II, more direct measures of economic performance such as quarterly GDP or monthly indicators of economic activity are not readily available for many countries in our sample, especially LICs. Despite this challenge, we made an effort to compile a database of monthly economic indicators for both LICs and EMEs, relying on as many data sources as possible

This effort was motivated by two reasons. First, the need to complement and double check the findings based on our two indirect measures, namely mobility and nighttime lights. Second, and perhaps more importantly, to be able to make more direct inferences about the impact of IMF financing on economic performance.

The compilation of this dataset involved the following steps. To start, we searched for the best available measures of economic activity at monthly and/or quarterly frequency on the webpages of central banks, ministries of finance, and statistical agencies of all countries in our sample. We searched not only for standardized data repositories but also information from periodic publications such as monthly or quarterly statistical bulletins. For those countries where no suitable data was provided by the country authorities on their websites, we recurred to alternative data sources such as the IMF Direction of Trade Statistics (DOTS), the IMF Dissemination Standards Bulletin Board (DSBB), Eurostat, the Fed St. Louis FRED Economic Data, and regional central banks (for countries in currency unions).

Based on this granular search, we managed to collect high-frequency data for all countries in our sample. Unfortunately, we could not find data covering just one frequency or just one indicator across all countries. As a second step, and to the extent possible, we prioritized data at monthly frequency and focused on indicators that are unambiguous measures of economic activity. Our dataset covers three traditional measures of economic activity (GDP, monthly coincident indicators of GDP, and monthly or quarterly industrial production) and four less traditional measures at monthly or quarterly frequencies (imports, domestic credit, electricity consumption, and tourist arrivals). Despite this heterogeneity across indicators, all these measures are known to be strongly correlated with business cycles.

As shown in the first block of Table AI.4 below, over half of the indicators collected are available at monthly frequency in the overall sample, with 60 percent for funded countries and just over 40 percent for the unfunded ones. As for the type of indicator, the three direct measures of economic activity account for three-quarters, two-thirds and over four-fifths of the total, and across funded and unfunded countries,

respectively (middle block of Table AI.4). Therefore, the dataset is reasonably well represented in terms of monthly frequency and indicators conveying good information on the state of the economy.

The third step comprised of curating and treating the raw data. This involved trimming down extreme observations, adjusting for seasonality whenever applicable, and deflating nominal amounts (e.g., imports, domestic credit). Quarterly observations were interpolated to monthly frequency using cubic spline interpolation. This method tends to yield smaller interpolation errors and lower oscillation between points compared with alternative techniques such as polynomial interpolation. Therefore, the final data used in the regressions was seasonally adjusted (by the official sources or the authors), not subject to the influence of outliers, expressed in real terms, and covering all months from December 2016 to June 2022. We set December 2016 as our base period and normalized all final indicators to December 2016=100.

In the fourth and final step we used our knowledge of the data, the extent of the data treatment applied and our judgment to assign a rating to each selected indicator. This rating reflects not only our perceptions about the quality of the data but also the extent to which the data is adequate for our empirical analysis. A “strong” rating was assigned to indicators that to our knowledge represents the best measure of economic activity and are available over the entire sample period at monthly frequency (e.g., coincident indicator of GDP). A “medium” rating was assigned to indicators with good informational content and time coverage but only available at quarterly frequency (e.g., GDP). A “weak” rating mostly covers the four indirect measures of economic activity, especially those that were only available at quarterly frequency and/or required important data treatment (e.g., imports). Despite our conservative rating strategy, only about a third of the indicators were assessed as weak, both in the overall sample and across the country groups (Table AI.4, last block).

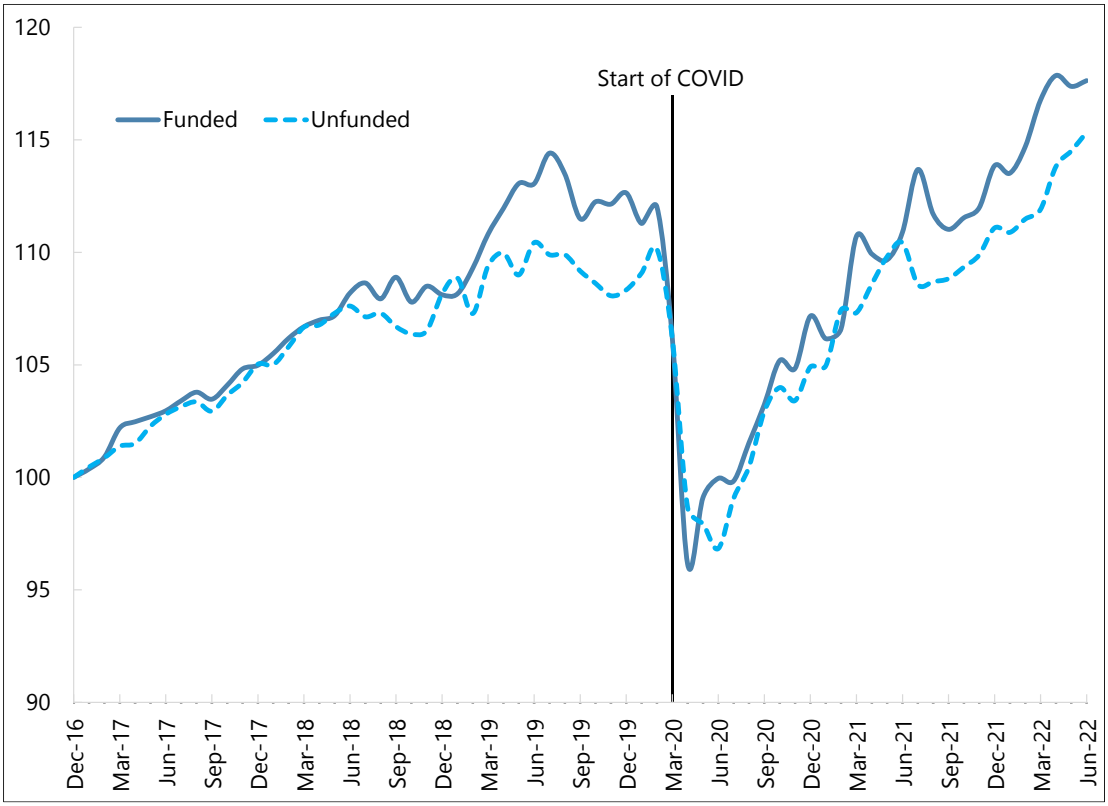
Table AI.4: Direct Measures of Economic Activity at High-Frequency

Indicator Characteristics	Funded countries	Unfunded countries	Full sample
Frequency of raw data	85	49	134
Monthly	51	21	72
Quarterly	34	28	62
Indicator type	85	49	134
Coincident indicator of GDP	14	6	20
GDP	27	21	48
Industrial production	12	3	15
Imports	16	14	30
Domestic credit	7	1	8
Electricity consumption	2	0	2
Tourist arrivals	7	4	11
Data quality and adequacy	85	49	134
Strong	27	11	38
Medium	28	21	49
Weak	30	17	47

A closer look at the final data reveals that the typical country in each group was growing roughly at the same time pace before the onset of the COVID-19 pandemic. Economic activity fell sharply in both funded and unfunded countries when the pandemic hit in March 2020. Although the recovery from the pandemic initiated relatively quickly, owing to supportive domestic measures and external financing

including from the IMF, our direct data indicates that it took about two years for economic activity to recover to pre-pandemic levels, with the group of unfunded countries posting a somewhat slower recovery (Figure AI.1). The overall behavior of our direct measure of economic activity, both before and during the pandemic, is roughly comparable to that of most indicators of mobility and nighttime lights (see Section III and Annex II).

Figure AI.1: Direct Measure of Monthly Economic Activity, Dec 2016–Jun 2022



Annex II. Additional Descriptive Analysis

Figure AII.1: Mobility at Different Economic Spaces, Jan 2020–Jan 2022

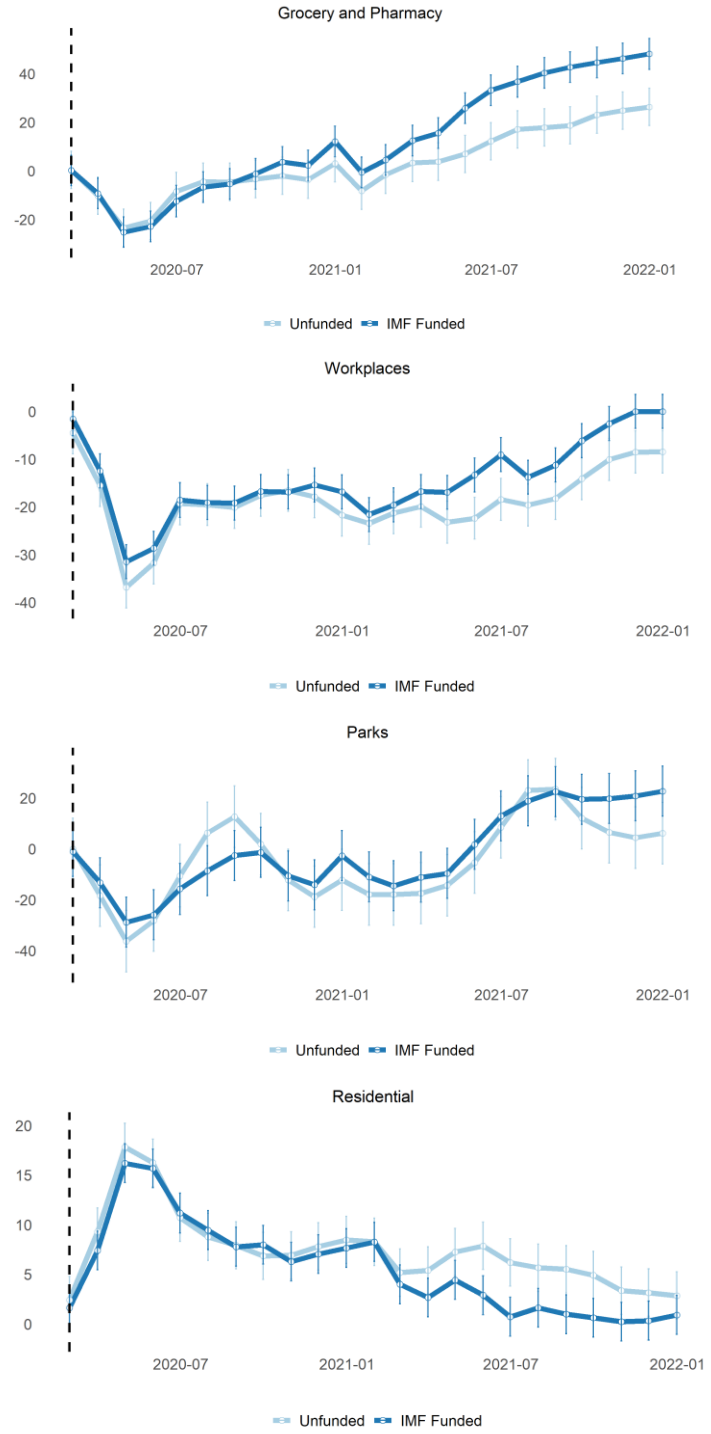
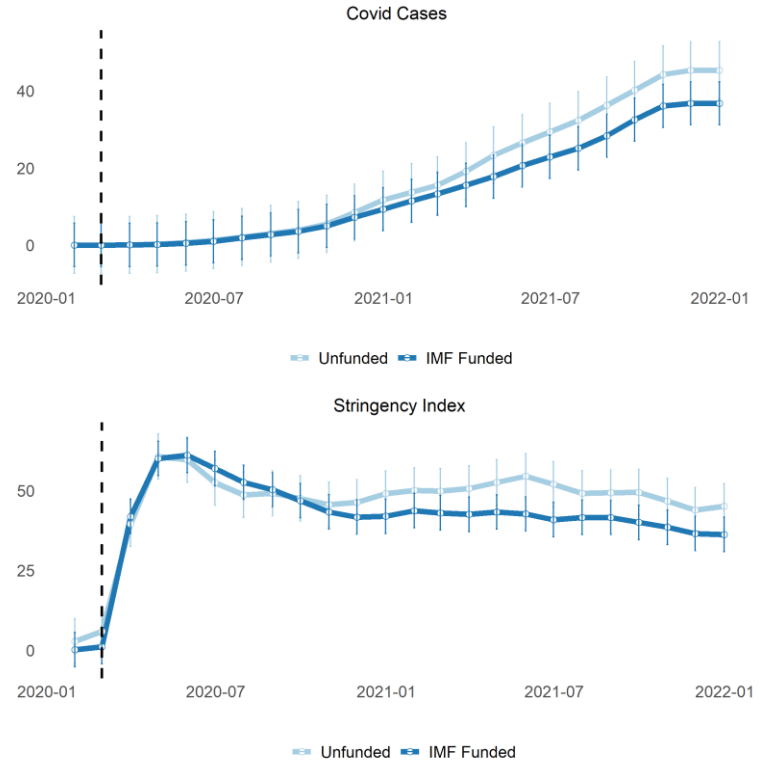


Figure AII.2: Measures of Severity of Pandemic and Lockdowns, Jan 2020–Jan 2022



Annex III. Additional Regression Analysis

Including country group-specific controls

Table AIII.1: Country group-specific controls: Economic Activity Index

	Dependent variable:		
	Economic Activity Index (Dec 2016 = 100)		
	(1)	(2)	(3)
IMF Disbursement (log)	0.361**	0.532***	0.601***
	(0.167)	(0.166)	(0.161)
Cumulative cases (log)	-0.309	-0.467**	-0.424**
	(0.215)	(0.215)	(0.210)
Stringency Index	-0.190***	-0.188***	-0.183***
	(0.017)	(0.017)	(0.016)
Reserves (months of import)	-0.745***	-0.671***	-0.942***
	(0.191)	(0.191)	(0.191)
WB, MDB funds (% of GDP)	-2.570***	-2.616***	-2.704***
	(0.263)	(0.264)	(0.262)
Country FE	Yes	Yes	Yes
Month FE X Income	Yes	No	No
Month FE X Gov Effective	No	Yes	No
Month FE X Rule of Law	No	No	Yes
Observations	3,130	3,130	3,130
R^2	0.795	0.794	0.798
Adjusted R^2	0.787	0.786	0.790
Residual Std. Error	15.416	15.460	15.311
Note:			*p**p***p<0.01

Alternative timing of disbursement: IMF financing in April–June 2020

Table AIII.2: IMF Financing in April–June 2020: Mobility

	Dependent variable:							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (log)	1.249***	1.104***	1.538***	1.407***	1.671***	1.714***	0.415*	0.483*
	(0.316)	(0.321)	(0.370)	(0.378)	(0.358)	(0.366)	(0.248)	(0.253)
Cumulative cases (log)	-2.152***	-2.361***	-0.160	-0.250	-1.795***	-1.746***	-1.378***	-1.425***
	(0.378)	(0.382)	(0.443)	(0.449)	(0.429)	(0.436)	(0.298)	(0.303)
Stringency Index	-0.525***	-0.519***	-0.437***	-0.436***	-0.618***	-0.620***	-0.331***	-0.325***
	(0.030)	(0.030)	(0.035)	(0.036)	(0.034)	(0.035)	(0.024)	(0.024)
Reserves (months of import)		-0.034		0.348		-0.038		-0.531*
		(0.375)		(0.442)		(0.429)		(0.296)
WB, MDB funds (% of GDP)		1.350***		0.707		-0.335		0.107
		(0.383)		(0.451)		(0.438)		(0.302)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155	1,153	1,153
R^2	0.785	0.788	0.779	0.780	0.794	0.795	0.684	0.685
Adjusted R^2	0.770	0.773	0.764	0.764	0.780	0.780	0.661	0.662
Residual Std. Error	11.170	11.115	13.100	13.091	12.686	12.694	8.763	8.758

Note: *p<0.1, **p<0.05, ***p<0.01

Table AIII.3: IMF Financing in April–June 2020: Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.012***	0.008*	3.385***	2.801***
	(0.004)	(0.004)	(0.668)	(0.705)
Cumulative cases (log)	-0.019***	-0.018***	-2.635***	-2.427***
	(0.006)	(0.006)	(0.901)	(0.908)
Stringency Index	0.001	0.001	0.147	0.134
	(0.001)	(0.001)	(0.094)	(0.094)
Reserves (months of import)		0.011**		1.543*
		(0.005)		(0.832)
WB, MDB funds (% of GDP)		0.012*		2.036*
		(0.007)		(1.160)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	1,648	1,648	1,648	1,648
R^2	0.982	0.982	0.721	0.723
Adjusted R^2	0.981	0.981	0.705	0.706
Residual Std. Error	0.259	0.258	41.125	41.053
Note:				*p<0.1, **p<0.05, ***p<0.01

Table AIII 4: IMF Financing in April–June 2020: Economic Activity Index

	Dependent variable:	
	Economic Activity Index (Dec 2016 = 100)	
	(1)	(2)
IMF Disbursement (log)	0.714***	1.490***
	(0.215)	(0.211)
Cumulative cases (log)	1.202***	1.262***
	(0.289)	(0.276)
Stringency Index	0.121***	0.121***
	(0.028)	(0.027)
Reserves (months of import)		-0.849***
		(0.259)
WB, MDB funds (% of GDP)		-4.345***
		(0.319)
Country FE	Yes	Yes
Month FE	Yes	Yes
Observations	1,985	1,985
R^2	0.819	0.838
Adjusted R^2	0.810	0.829
Residual Std. Error	14.023	13.292
Note:		*p<0.1, **p<0.05, ***p<0.01

Scaling the treatment variable

Table AIII.5: IMF Disbursement in Percent of GDP: Mobility

	Dependent variable:							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (% of GDP)	3.573***	2.826***	3.125***	3.002***	2.968***	2.902***	1.346***	1.677***
	(0.563)	(0.582)	(0.708)	(0.736)	(0.647)	(0.670)	(0.443)	(0.457)
Cumulative cases (log)	-2.997***	-3.008***	-1.891***	-1.719***	-3.046***	-2.766***	-1.535***	-1.740***
	(0.309)	(0.314)	(0.389)	(0.397)	(0.355)	(0.362)	(0.245)	(0.249)
Stringency Index	-0.488***	-0.490***	-0.429***	-0.434***	-0.530***	-0.538***	-0.284***	-0.277***
	(0.025)	(0.025)	(0.032)	(0.032)	(0.029)	(0.029)	(0.020)	(0.020)
Reserves (months of import)		0.520**		0.629**		0.923***		-0.872***
		(0.229)		(0.290)		(0.264)		(0.180)
WB, MDB funds (% of GDP)		1.121***		-0.328		-0.730**		0.113
		(0.310)		(0.392)		(0.357)		(0.244)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,657	1,657	1,657	1,657	1,657	1,657	1,655	1,655
R^2	0.825	0.827	0.810	0.811	0.819	0.820	0.702	0.707
Adjusted R^2	0.813	0.816	0.798	0.799	0.807	0.809	0.683	0.688
Residual Std. Error	10.672	10.605	13.426	13.413	12.262	12.214	8.396	8.338
Note:								*p<0.1, **p<0.05, ***p<0.01

Table AIII.6: IMF Disbursement in Percent of GDP: Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Disbursement (% of GDP)	0.025***	0.016*	2.791**	1.155
	(0.008)	(0.008)	(1.253)	(1.301)
Cumulative cases (log)	-0.024***	-0.022***	-3.217***	-2.935***
	(0.004)	(0.004)	(0.651)	(0.656)
Stringency Index	-0.0002	-0.0001	0.003	0.011
	(0.0004)	(0.0004)	(0.065)	(0.064)
Reserves (months of import)		0.011***		1.675***
		(0.003)		(0.466)
WB, MDB funds (% of GDP)		0.010**		2.194***
		(0.005)		(0.770)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,619	2,619	2,619	2,619
R^2	0.984	0.984	0.714	0.717
Adjusted R^2	0.983	0.983	0.700	0.702
Residual Std. Error	0.225	0.224	34.682	34.531
Note:				*p<0.1, **p<0.05, ***p<0.01

Table AIII 7: IMF Disbursement in Percent of GDP: Economic Activity Index

	Dependent variable:	
	Economic Activity Index (Dec 2016 = 100)	
	(1)	(2)
IMF Disbursement (% of GDP)	0.389	1.801***
	(0.448)	(0.463)
Cumulative cases (log)	0.414	0.266
	(0.253)	(0.252)
Stringency Index	0.031	0.031
	(0.024)	(0.024)
Reserves (months of import)		0.086
		(0.196)
WB, MDB funds (% of GDP)		-2.834***
		(0.267)
Country FE	Yes	Yes
Month FE	Yes	Yes
Observations	3,130	3,130
R^2	0.802	0.809
Adjusted R^2	0.792	0.800
Residual Std. Error	15.231	14.952
Note:		*p<0.1, **p<0.05, ***p<0.01

Table AIII.8: IMF Disbursement in Percent of Quota: Mobility

	Dependent variable:							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (percent of quota)	0.054***	0.048***	0.079***	0.078***	0.062***	0.061***	0.030***	0.033***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.009)	(0.006)	(0.006)
Cumulative cases (log)	-2.908***	-2.933***	-1.757***	-1.595***	-2.944***	-2.670***	-1.495***	-1.708***
	(0.313)	(0.317)	(0.389)	(0.398)	(0.358)	(0.364)	(0.248)	(0.252)
Stringency Index	-0.484***	-0.487***	-0.433***	-0.438***	-0.528***	-0.536***	-0.286***	-0.278***
	(0.026)	(0.025)	(0.032)	(0.032)	(0.029)	(0.029)	(0.020)	(0.020)
Reserves (months of import)		0.522**		0.546*		0.888***		-0.893***
		(0.229)		(0.287)		(0.263)		(0.181)
WB, MDB funds (% of GDP)		1.195***		-0.400		-0.737**		0.145
		(0.306)		(0.383)		(0.351)		(0.241)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,612	1,612	1,612	1,612	1,612	1,612	1,610	1,610
R2	0.827	0.830	0.817	0.818	0.823	0.824	0.706	0.710
Adjusted R2	0.816	0.818	0.805	0.806	0.811	0.813	0.687	0.691
Residual Std. Error	10.694	10.613	13.318	13.309	12.233	12.186	8.429	8.367

Note: *p**p***p<0.01

Table AIII.9: IMF Disbursement in Percent of Quota: Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Disbursement (percent of quota)	0.0002	0.0001	0.047**	0.031*
	(0.0001)	(0.0001)	(0.018)	(0.019)
Cumulative cases (log)	-0.024***	-0.021***	-3.171***	-2.836***
	(0.004)	(0.004)	(0.670)	(0.676)
Stringency Index	-0.0004	-0.0003	-0.023	-0.009
	(0.0004)	(0.0004)	(0.066)	(0.066)
Reserves (months of import)		0.012***		1.673***
		(0.003)		(0.475)
WB, MDB funds (% of GDP)		0.010**		1.962**
		(0.005)		(0.765)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,543	2,543	2,543	2,543
R2	0.983	0.983	0.716	0.719
Adjusted R2	0.982	0.982	0.702	0.704
Residual Std. Error	0.227	0.226	34.928	34.785
Note:				*p**p***p<0.01

Table AIII.10: IMF Disbursement in Percent of Quota: Economic Activity Index

	Dependent variable:	
	Economic Activity Index (Dec 2016 = 100)	
	(1)	(2)
IMF Disbursement (percent of quota)	0.012	0.023***
	(0.008)	(0.008)
Cumulative cases (log)	0.274	0.090
	(0.259)	(0.259)
Stringency Index	0.034	0.032
	(0.025)	(0.024)
Reserves (months of import)		0.026
		(0.200)
WB, MDB funds (% of GDP)		-2.622***
		(0.262)
Country FE	Yes	Yes
Month FE	Yes	Yes
Observations	3,040	3,040
R^2	0.780	0.788
Adjusted R^2	0.770	0.778
Residual Std. Error	15.291	15.032
Note:		*p**p***p<0.01

Alternative definition of the treatment: IMF Commitments

Table AIII.11: IMF Commitments: Mobility

	Dependent variable:							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Commitment (log)	1.031***	0.860***	1.084***	1.009***	1.153***	1.072***	0.252	0.344**
	(0.197)	(0.198)	(0.247)	(0.250)	(0.225)	(0.228)	(0.155)	(0.156)
Cumulative cases (log)	-3.095***	-3.108***	-1.988***	-1.833***	-3.146***	-2.884***	-1.563***	-1.786***
	(0.311)	(0.315)	(0.389)	(0.398)	(0.355)	(0.362)	(0.245)	(0.250)
Stringency Index	-0.480***	-0.484***	-0.421***	-0.427***	-0.522***	-0.530***	-0.282***	-0.274***
	(0.025)	(0.025)	(0.032)	(0.032)	(0.029)	(0.029)	(0.020)	(0.020)
Reserves (months of import)		0.533**		0.628**		0.907***		-0.840***
		(0.230)		(0.290)		(0.264)		(0.181)
WB, MDB funds (% of GDP)		1.335***		-0.113		-0.535		0.261
		(0.304)		(0.384)		(0.349)		(0.240)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,657	1,657	1,657	1,657	1,657	1,657	1,655	1,655
R^2	0.823	0.827	0.810	0.811	0.819	0.821	0.701	0.705
Adjusted R^2	0.812	0.815	0.798	0.798	0.808	0.809	0.682	0.686
Residual Std. Error	10.716	10.621	13.427	13.415	12.242	12.201	8.414	8.361

Note: *p<0.1, **p<0.05, ***p<0.01

Table AIII.12: IMF Commitments: Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Commitment (log)	0.012***	0.010***	2.151***	1.794***
	(0.003)	(0.003)	(0.401)	(0.411)
Cumulative cases (log)	-0.025***	-0.022***	-3.297***	-2.996***
	(0.004)	(0.004)	(0.647)	(0.654)
Stringency Index	-0.0001	-0.0001	0.018	0.026
	(0.0004)	(0.0004)	(0.064)	(0.064)
Reserves (months of import)		0.011***		1.533***
		(0.003)		(0.464)
WB, MDB funds (% of GDP)		0.009*		1.728**
		(0.005)		(0.757)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,619	2,619	2,619	2,619
R^2	0.984	0.984	0.717	0.719
Adjusted R^2	0.983	0.983	0.703	0.705
Residual Std. Error	0.225	0.224	34.518	34.405
Note:				*p<0.1, **p<0.05, ***p<0.01

Table AIII.13: IMF Commitments: Economic Activity Index

	Dependent variable:	
	Economic Activity Index (Dec 2016 = 100)	
	(1)	(2)
IMF Commitment (log)	0.746***	1.023***
	(0.165)	(0.165)
Cumulative cases (log)	0.406	0.222
	(0.252)	(0.251)
Stringency Index	0.035	0.034
	(0.024)	(0.024)
Reserves (months of import)		0.054
		(0.195)
WB, MDB funds (% of GDP)		-2.774***
		(0.259)
Country FE	Yes	Yes
Month FE	Yes	Yes
Observations	3,130	3,130
R^2	0.803	0.811
Adjusted R^2	0.794	0.801
Residual Std. Error	15.181	14.895
Note:		*p<0.1, **p<0.05, ***p<0.01

Clustered standard errors

Table AIII.14: Clustered standard errors: Mobility

	Dependent variable:							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (log)	1.180***	1.069***	1.400***	1.370***	1.460***	1.445***	0.670**	0.713***
	(0.284)	(0.293)	(0.401)	(0.403)	(0.410)	(0.407)	(0.275)	(0.262)
Cumulative cases (log)	-3.133***	-3.170***	-2.015	-1.869	-3.151**	-2.873**	-1.660**	-1.851**
	(0.900)	(0.867)	(1.505)	(1.463)	(1.226)	(1.202)	(0.756)	(0.773)
Stringency Index	-0.487***	-0.489***	-0.433***	-0.438***	-0.531***	-0.538***	-0.290***	-0.284***
	(0.061)	(0.058)	(0.086)	(0.085)	(0.076)	(0.074)	(0.048)	(0.048)
Reserves (months of import)		0.439		0.594		0.924*		-0.781**
		(0.463)		(0.872)		(0.488)		(0.348)
WB, MDB funds (% of GDP)		1.410**		-0.116		-0.694		0.094
		(0.607)		(0.785)		(0.926)		(0.485)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,657	1,657	1,657	1,657	1,657	1,657	1,655	1,655
R^2	0.831	0.834	0.818	0.819	0.821	0.822	0.715	0.718
Adjusted R^2	0.820	0.823	0.807	0.807	0.809	0.811	0.696	0.700
Residual Std. Error	11.038	10.942	13.702	13.690	12.659	12.606	9.039	8.989
Note:								*p**p***p<0.01

Table AIII.15: Clustered standard errors: Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.010**	0.008*	1.672	1.339
	(0.005)	(0.005)	(1.062)	(0.951)
Cumulative cases (log)	-0.029***	-0.026***	-3.270***	-2.944***
	(0.007)	(0.007)	(1.002)	(0.957)
Stringency Index	-0.0001	-0.0001	-0.008	0.001
	(0.001)	(0.001)	(0.094)	(0.095)
Reserves (months of import)		0.013***		1.531***
		(0.004)		(0.531)
WB, MDB funds (% of GDP)		0.011		1.783
		(0.008)		(1.284)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,619	2,619	2,619	2,619
R^2	0.975	0.975	0.716	0.718
Adjusted R^2	0.974	0.974	0.701	0.704
Residual Std. Error	0.279	0.278	34.587	34.458
Note:				*p**p***p<0.01

Table AIII.16: Clustered standard errors: Economic Activity Index

	Dependent variable:			
	Economic Activity (Index)		Economic Activity (log)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.742*	1.013**	0.015	0.019
	(0.404)	(0.396)	(0.011)	(0.013)
Cumulative cases (log)	0.379	0.191	0.037	0.033
	(0.915)	(0.903)	(0.030)	(0.030)
Stringency Index	0.035	0.033	0.003	0.003
	(0.082)	(0.080)	(0.003)	(0.003)
Reserves (months of import)		0.087		-0.004
		(0.496)		(0.009)
WB, MDB funds (% of GDP)		-2.787***		-0.042
		(1.003)		(0.041)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	3,130	3,130	3,130	3,130
R^2	0.803	0.811	0.656	0.659
Adjusted R^2	0.794	0.802	0.639	0.643
Residual Std. Error	15.179	14.892	0.437	0.435
Note:				*p**p***p<0.01

Alternative Financing Type: Emergency financing only

Table AIII.17: IMF Emergency Financing: Mobility

	Dependent variable:							
	Retail		Grocery		Transit		Workplaces	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMF Disbursement (log)	1.003***	1.006***	0.883***	0.980***	1.591***	1.836***	0.301	0.507**
	(0.254)	(0.262)	(0.243)	(0.252)	(0.281)	(0.291)	(0.204)	(0.209)
Cumulative cases (log)	-2.895***	-2.964***	-1.932***	-1.936***	-2.853***	-2.820***	-2.056***	-2.077***
	(0.332)	(0.332)	(0.318)	(0.318)	(0.368)	(0.367)	(0.268)	(0.267)
Stringency Index	-0.479***	-0.468***	-0.321***	-0.318***	-0.536***	-0.534***	-0.272***	-0.263***
	(0.028)	(0.028)	(0.026)	(0.027)	(0.031)	(0.031)	(0.022)	(0.022)
Reserves (months of import)		-1.086**		-0.633		-0.936**		-1.482***
		(0.429)		(0.411)		(0.475)		(0.342)
WB, MDB funds (% of GDP)		1.078**		-0.254		-1.327**		-0.400
		(0.520)		(0.498)		(0.575)		(0.415)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,192	1,192	1,192	1,192	1,192	1,192	1,190	1,190
R^2	0.794	0.795	0.815	0.815	0.796	0.798	0.690	0.695
Adjusted R^2	0.779	0.781	0.802	0.802	0.782	0.784	0.668	0.673
Residual Std. Error	10.239	10.203	9.788	9.784	11.336	11.295	8.203	8.134
Note:								*p**p***p<0.01

Table AIII.18: IMF Emergency Financing: Nighttime Lights

	Dependent variable:			
	Night Lights (log)		Night Lights (% change from baseline)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.015***	0.012***	3.075***	2.181***
	(0.004)	(0.004)	(0.622)	(0.666)
Cumulative cases (log)	-0.012**	-0.011*	-2.479***	-2.115**
	(0.006)	(0.006)	(0.854)	(0.857)
Stringency Index	0.001	0.001	0.063	0.053
	(0.001)	(0.001)	(0.088)	(0.088)
Reserves (months of import)		0.003		2.442**
		(0.007)		(1.069)
WB, MDB funds (% of GDP)		0.022**		4.405***
		(0.011)		(1.589)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	1,787	1,787	1,787	1,787
R^2	0.979	0.979	0.718	0.720
Adjusted R^2	0.977	0.977	0.702	0.704
Residual Std. Error	0.268	0.268	40.112	39.945
Note:				*p**p***p<0.01

Table AIII.19: IMF Emergency Financing: Economic Activity Index

	Dependent variable:			
	Economic Activity (Index)		Economic Activity (log)	
	(1)	(2)	(3)	(4)
IMF Disbursement (log)	0.652***	1.461***	0.006**	0.017***
	(0.171)	(0.168)	(0.002)	(0.002)
Cumulative cases (log)	0.426*	-0.149	0.012***	0.005
	(0.221)	(0.211)	(0.003)	(0.003)
Stringency Index	0.027	0.037*	0.001**	0.001***
	(0.022)	(0.021)	(0.0003)	(0.0003)
Reserves (months of import)		-2.486***		-0.035***
		(0.269)		(0.004)
WB, MDB funds (% of GDP)		-4.148***		-0.053***
		(0.349)		(0.005)
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,193	2,193	2,193	2,193
R^2	0.787	0.813	0.754	0.781
Adjusted R^2	0.776	0.803	0.742	0.770
Residual Std. Error	11.908	11.150	0.171	0.161

Note: *p**p***p<0.01

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