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The Catalytic Impact of IMF Lending on Official Development Assistance

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ABSTRACT: This paper explores the catalytic impact of IMF lending to Low-Income Countries on Official Development Assistance (ODA) during 1990-2019. It disentangles the effect on the amounts of ODA on countries' participation in IMF programs ("extensive margin") and the size of the IMF-supported program ("intensive margin"). To address selection biases, we rely on the interaction of past IMF program participation and IMF liquidity as an instrument for program participation and employ the review of access limits as an instrument for the size of disbursements. We document that a one percentage point (pp) of GDP increase in IMF disbursements catalyzes additional ODA of 2.7 pp of GDP. In addition, we find that IMF disbursements catalyze ODA mostly from multilateral donors (1.3 pp of GDP) and to lesser extent from traditional bilateral donors (0.6 pp of GDP). Among multilateral donors, the strongest effect is on World Bank disbursements, followed by the EU. Finally, we document that catalytic effects on ODA have decreasing returns to large IMF disbursement amounts.

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1 Introduction

Official Development Assistance (ODA) represents a primary source of external financing for Low-Income Countries (LICs). In contrast to emerging markets, LICs' domestic savings are typically low and their access to portfolio flows is limited (International Monetary Fund, 2023b). In 2019, international development partners disbursed around USD 52.4 billion of ODA to LICs, representing 6.3 percent of GDP for the average LIC.[1]

In situations where external balances come under pressure, LICs often turn to the International Monetary Fund (IMF) for financial support. To address external pressures of individual LICs, IMF-supported programs lay out an agreed roadmap for policy actions and structural reforms complemented by granting financing to mitigate the adverse effects of the adjustment policies. In doing so, these IMF-supported programs and the related IMF financing are expected to catalyze external financing from multilateral and official bilateral donors. The importance of the magnitude of the catalytic impact of IMF lending is underscored by LICs' large financing needs as they strive to achieve the Sustainable Development Goals in the aftermath of the COVID-19 pandemic, and amid the tightening of financial conditions in advanced economies in response to the post-pandemic surge in inflation.

In this paper we analyze the catalytic effect of IMF programs on ODA for LICs. We ask the following questions: Is there a catalytic effect of IMF programs on ODA? If so, how large is it and how has it evolved over the past decades? Which donors contribute the most and through which aid type (grants vs concessional loans)? Does the size of IMF disbursements matter for the amounts catalyzed?

Before answering these questions, it is important to address important identification challenges for IMF program participation: selection bias. Countries typically borrow from the IMF when they are facing economic hardship. This fact, combined with the alignment between LICs, donors, and the IMF means that econometric methods that do not correctly account for the non-random selection of LICs requesting IMF programs will likely lead to biased estimation results. Some studies have attempted to address selection bias by relying on *selection on observables* methods to identify the catalytic effects of IMF programs (Bird and Rowlands, 2007).

Instead, in this paper we rely on two instrumental variables (IVs) to address different dimensions of selection bias. The first one addresses potential biases of program participation. Following Lang (2021), Gehring and Lang (2020) and Krahnke (2023), we employ an instrument that combines cross-sectional variation in a country's probability of requesting an IMF program (based on past requests) and the temporal variation in the IMF's liquid

[1] Own estimations based on OECD ODA database.

resources. The second IV addresses potential biases of program size. Larger amounts of IMF lending and ODA are likely to be provided in tandem to countries in deep economic crises. As in Krahnke (2023), we use the IMF's pre-determined institutional changes to borrowing limits, also known as 'access limits', as an IV for lending amounts. Variation in these IVs are largely driven by pre-determined periodic revisions to the IMF rules and regulations (such as the review of country quotas), which are exogenous to the traditional determinants of ODA in LICs.

Equipped with these IVs, we estimate the impact of IMF disbursements on the amounts of ODA inflows (as percent of GDP) using a country-year panel of 63 LICs over the 1990-2019 period. Unlike other studies that use binary variables to capture the impact of IMF programs, we estimate the impact of IMF disbursements to decouple the extensive margin (program participation) from the intensive margin (program size). These disbursement data, sourced from IMF administrative accounts, correspond to all traditional IMF arrangements (such as the Extended and Stand-by Credit Facilities).[2]

Our findings present evidence that IMF lending catalyzes ODA. We find that a one percentage point (henceforth pp) increase in IMF disbursements (relative to GDP) catalyzes an increase in ODA by 2.7 pp of GDP. Given the average size of annual disbursements (0.8 pp of GDP), the average country in an IMF program is expected to observe additional ODA flows of 2.2 pp of GDP per year. In other words, for each dollar disbursed, the IMF would cover (*ex-post*) approximately 27 percent of total donor flows in active programs.[3] We also document that the magnitude of the catalytic effects in LICs has remained broadly stable throughout the 1990-2019 period.

We find that IMF programs catalyze most ODA flows from multilateral donors (1.4 pp of GDP) and traditional bilateral donors (0.7 pp of GDP). As expected, among multilaterals the largest contributions are from the World Bank followed by the European Union. Our findings also show that these catalytic effects are more pronounced for grants than for concessional loans.

We find that larger disbursements catalyze larger ODA flows. When decomposing between program participation effects and lending amounts (identifying each margin with our IVs), we report that the size of disbursements is, on average, more (statistically) relevant than simple program participation.[4] When comparing across active programs, we also document that larger disbursements catalyze more ODA. However, we find a nonlinear effect between

[2]We only include programs with upper credit tranche quality conditionality. In other words, all emergency financing arrangements are excluded.

[3]If 1 pp of GDP in IMF disbursements catalyzes 2.7 GDP points of ODA, then the IMF would be covering $1/(1+2.7) \approx 27$ percent of total new donor flows to the average program country.

[4]Note that this finding is not informative about the catalytic impact of IMF programs not included in this study, including non-financial ones.

the two, implying there are diminishing catalytic effects in the amount of IMF financing.

This paper builds on the limited literature which analyses the impact of traditional IMF-supported programs on ODA for LICs. The few other papers that have looked into this topic have relied on *selection on observables* methods. Gündüz and Crystallin (2018) adopt a Propensity Score Matching and find that IMF programs increase net ODA disbursements by 2.4 percent of GDP. Along the same line, Schiavone and Maurini (2023) use an entropy balancing method and report that IMF programs boost ODA in LICs by 1.6 pp of GDP per year. Complementing the findings of traditional programs, Cohen-Setton and Toni (2024) also find catalytic effects for IMF emergency financing throughout the COVID-19 pandemic. Other studies, which do not have an explicit IV strategy, also find a strong positive correlation between traditional IMF programs and ODA (Bird and Rowlands, 2007; Dabla-Norris, Minoiu, and Zanna, 2010; Stubbs, Kentikelenis, and King, 2016).

We also contribute to a wider range of studies that have explored the impact of IMF programs on capital flows in emerging market (non-LIC) economies (Díaz-Cassou, García-Herrero, and Molina, 2006; Erce and Riera-Crichton, 2015). Some studies find that IMF programs have played a catalytic role depending on borrower's initial conditions (Mody and Saravia, 2006), while others have reported elusive effects (Jensen, 2004). Krahnke (2023) and Maurini and Schiavone (2021) finds that large IMF lending amounts play an anti-catalytic effect on private capital flows in emerging market economies. Additional studies have reported that IMF programs have a catalytic impact on Foreign Direct Investment flows (Al-Sadiq, 2015; Woo, 2013) and lower the cost of borrowing (Chahine, Panizza, and Suedekum, 2024).

The remainder of the paper is organized as follows. Section 2 describes stylized facts regarding ODA and IMF programs in LICs. Section 3 presents the methodology to estimate the catalytic effects, including the identification strategy and the construction of the IVs. Section 4 details the data employed for the econometric analysis. Section 5 describes the main econometric results while section 6 presents a sensitivity analysis of the findings. Finally, section 7 provides a summary and conclusions.

2 ODA and IMF Lending to LICs: Stylized Facts

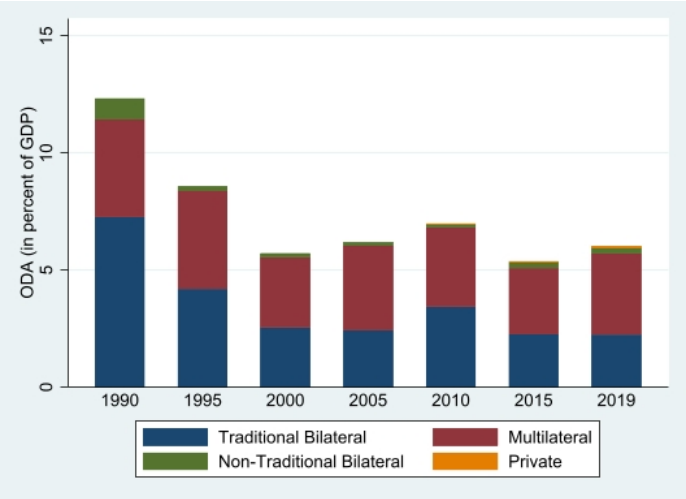
This section discusses stylized facts about ODA and IMF lending to LICs and the positive sorting between the two.

ODA represents a principal source of external financing for LICs, which are constrained by their limited access to private capital markets and have low domestic savings. By helping to address external financing needs, ODA can limit the size of the needed fiscal adjustments thereby helping to protect the poorest and most vulnerable. In this sense, ODA can act

as a buffer aiding the recipient country facing an economic shock (Dabla-Norris, Minoiu, and Zanna, 2010). While the absolute amount of ODA flows to LICs has increased from USD 13.4 billion to 52.4 billion from 1990-2019, its magnitude in relation to the size of the economy for the average LIC has nearly halved, falling from 12.7 to 6.3 pp of GDP over the same period. Figure 1 depicts total ODA flows to LICs (in percent of GDP) broken down by donor type in 5-year intervals from 1990 to 2019. Although ODA flows have declined in real terms, they have consistently remained above 5 pp of GDP, thereby providing important financing to LICs.

The composition of ODA to LICs has shifted over time. The share provided by traditional bilateral donors fell from 63 to 43 percent of ODA between 1990 and 2019 while conversely the multilateral donors' share of ODA rose from 32 to 51 percent. The share of ODA provided by non-traditional bilateral donors showed an upward trajectory since 2009 but it still remained small at 4 percent of total ODA flows in 2019.[5]

Figure 1: ODA Flows (in percent of GDP) to LICs



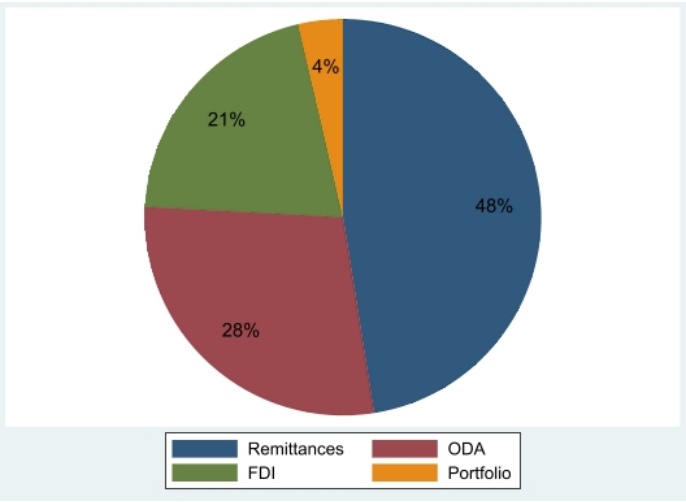
Source: Authors' estimates based on the OECD ODA database (OECD, 2023).

LICs significantly rely on ODA flows to balance their external financing needs. Figure 2 shows the composition of external financing flows to LICs in 2019. ODA and remittances represent 28 percent and 48 percent of external financing flows, respectively. By contrast,

[5]Data on non-traditional bilateral donors only captures non-OECD countries that voluntarily report to the OECD Development Assistance Committee. This excludes important partners such as China. Data on non-traditional bilateral donor support is thus likely to be an underestimate even though many Chinese financial flows may not meet the ODA criteria. See Appendix A for a full list of non-traditional bilateral donors that report to the OECD.

private capital flows, in the form of FDI and portfolio flows have expanded in past years but still account for less flows than ODA. FDI flows represent 21 percent of external financing flows. Reflecting LICs limited access to external capital markets, private portfolio flows made a small contribution to LICs external financing worth only 4 percent in 2019.

Figure 2: Composition of selected external financing flows to LICs in 2019



Source: Authors calculations based on OECD ODA database (OECD, 2023) and the World Bank's WDI (World Bank, 2024).

IMF concessional lending to LICs is designed to assist countries with protracted balance of payments needs. Its goal is to facilitate the implementation of economic policy actions to restore external balance while supporting strong growth and poverty reduction. The size of IMF lending to LICs is determined on a case-by-case basis taking into account the size of the balance of payments gap, the strength of the program, capacity to repay the IMF and the borrowing country's past record of policy implementation.

LICs often request IMF-supported programs when they suffer economic hardship and external sector pressures emerge. In IMF program negotiations, the program's size, length, schedule of disbursements and policy actions are discussed and agreed prior to its approval by the IMF's Executive Board. Once the program is approved, the policy actions envisaged in the program as well as the schedule and amount of disbursements are publicly communicated such that international investors and other development partners have clarity on the way forward. Disbursements over the duration of the program can be front-, even-, or back-loaded depending on each country's balance of payments situation and the phasing of the adjustment measures and the expected timing of their impact.

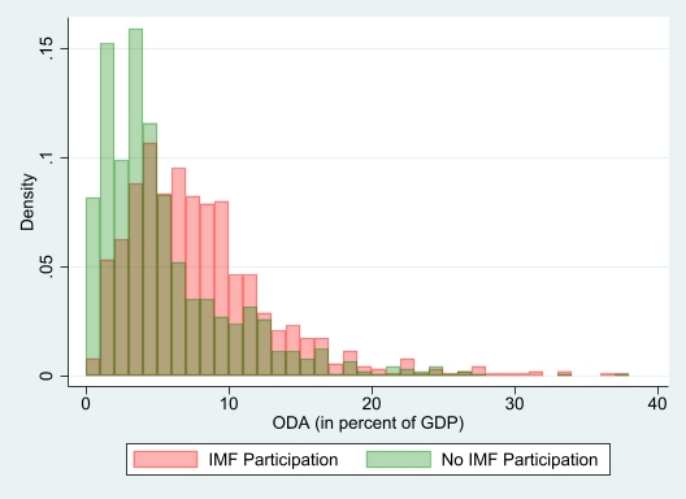
Prior to disbursing, the IMF's Executive Board verifies that the program is 'on-track' through formal program reviews. In most cases, the timing and amounts of disbursements follow the schedule agreed upon approval. However, in some cases the amount of financing may deviate. Amounts may be brought forward or delayed depending on macroeconomic conditions and progress on policy reforms/actions. In some cases, when countries encounter additional financing needs, they can request an 'augmentation'. Programs can go 'off-track' for various reasons. In those cases, program reviews are not completed and disbursements are stopped.

In this study we estimate the (ex-post) catalytic effect from IMF-supported programs. As per IMF institutional rules, the approval of a program request (and subsequent reviews) require the IMF's *financing assurances policy* to hold. This policy requires that an IMF-supported program has adequate external donor financing to fill program financing gaps, such that the program is (ex-ante) fully financed for the next 12 months and with good prospects for the remainder of the program period. This means that other donors, mainly the World Bank and other traditional bilateral and multilateral donors, should indicate that they will provide additional new financing to the member country to support the efforts to restore macroeconomic stability. Nonetheless, these indications from other donors are not binding. Some may not always materialize, whereas some donors may contribute throughout the program without prior announcement to the IMF. In this way, in this paper we refer to the catalytic effect as the (ex-post) materialized support from the donor community in response to the IMF financing.

The IMF's catalytic effect is expected to be achieved through two channels. First, the conditionality associated with an IMF program entails the implementation of a wide range of reforms which can both act as a signal regarding the authorities' intentions and strengthen the recipient government's ability to withstand economic shocks. Failure to comply with these conditions can lead to loss of financial assistance. The second channel is the direct provision of liquidity associated with an IMF program, which can ease the burden of adjustment to an economic shock (Bird and Rowlands, 2000; Bird and Rowlands, 2007; Stubbs, Kentikelenis, and King, 2016). Both channels can boost ODA as donors may perceive their aid to become more effective with the recipient country's enhanced resilience and more robust expected macro-economic outcomes. In this way, IMF-supported programs serve as a coordination mechanism amongst donors (Gündüz and Crystallin, 2018).

Participation in IMF programs and ODA are highly correlated in LICs. Figure 3 depicts the annual ODA-to-GDP ratio for LICs splitting the sample between LICs in and out of IMF-supported programs. On average LICs engaged in an IMF-supported program receive nearly double the annual amount of ODA (10.2 pp of GDP) compared to those that are not (5.8 pp of GDP). The ODA-to-GDP ratio varies widely across LICs and its distribution has a long right tail. As expected, ODA is positively correlated with

Figure 3: Distribution of ODA (in percent of GDP) across IMF program participation status



Note: Observations are country-year values.

IMF programs, as macroeconomic and structural reforms undertaken to address balance of payments pressures and boost growth and poverty reduction may trigger both engagement from the IMF and more ODA support from other donors.

Another way of visualizing this correlation is through time series. For example, Figure 4 shows that Guinea-Bissau participated in five IMF programs between 1990 and 2019. In each, the ODA-to-GDP ratio is on average higher in each program period compared to off-program years. The amount of ODA (net of debt relief) received was large, exceeding 20 pp of GDP in years prior to 2000. Similar dynamics are observed in Togo.

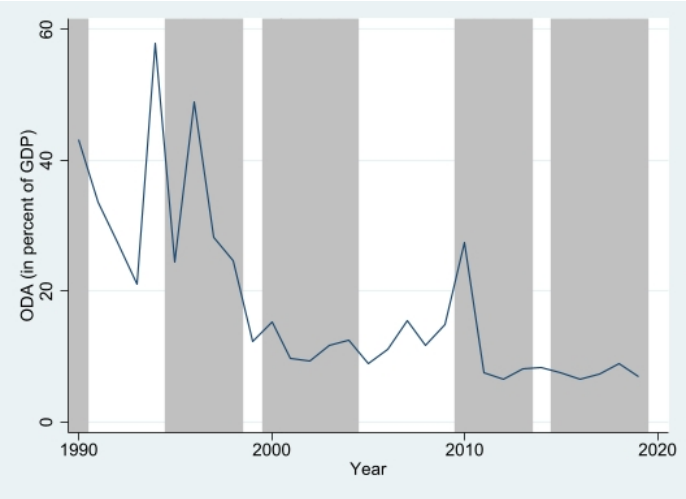
3 Methodology

This section discusses the econometric approach to identify the catalytic effects of IMF lending. Section 3.1 describes the identification strategy to address selection biases of program participation and size. Section 3.2 describes the econometric specifications.

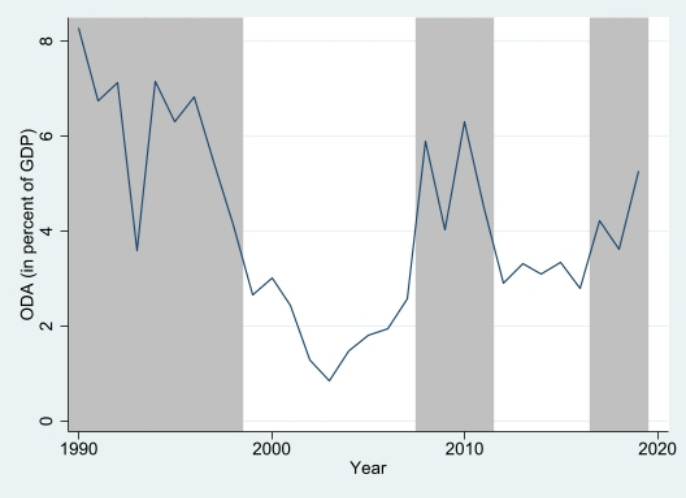
A simple OLS regression of ODA flows on IMF financing would most certainly deliver biased estimates. LICs typically turn to IMF lending when external financing needs are on the rise and alternative sources of financing are not available. On the other hand, LICs receive a continuous flow of ODA from multiple donors. As shown in Figure 3, these flows increase, on average, when countries are engaged in an IMF program. Therefore, it is

Figure 4: ODA (in percent of GDP) in selected countries (program participation in shaded areas)

Panel A. Guinea-Bissau



Panel B. Togo



Source: Authors' calculations based on OECD ODA database (OECD, 2023).

challenging to identify which ODA flows were actually catalyzed by IMF programs, and which ones were not.

The difficulty arises because the same drivers for a request of an IMF program could also potentially explain heightened receipt of ODA flows from other development partners, e.g., recessions, widening current account deficits, adverse terms of trade shocks, supporting a new reform minded government, to name a few. To provide a clear identification strategy of the catalytic impact of IMF programs we rely on IVs.

3.1 Identification Strategy

We build two IVs. One to address bias from selection into programs and another to address bias from program size. To this aim, we use the same IV approach described in Lang (2021), Gehring and Lang (2020), and Krahnke (2023).

The first IV that addresses bias from selection into programs comprises the interaction between past participation in IMF programs and temporal variation in IMF lending resources. Based on Lang (2021) and Krahnke (2023), we construct our first IV as

$$\text{IMFProbability}_{it} \times \log(\text{IMFLiquidity}_t), \tag{1}$$

which is the interaction between country i's specific probability of having participated in an IMF program in the past, $\text{IMFProbability}_{it}$, defined as past number of years under programs, and the (log of) disposable amounts of IMF resources that are available for lending, IMFLiquidity_t.[6]

The literature generally finds that past participation in IMF programs is a good predictor of future participation (Bird, Hussain, and Joyce, 2004; Sturm, Berger, and De Haan, 2005). One of the reasons put forward pertains to the balance of payments pressures caused by repayments to the IMF on earlier loans exacerbated by new domestic or external shocks, as is not uncommon among LICs (Conway, 2007). Another view points at 'recidivism' or political favoritism (Bird, Hussain, and Joyce, 2004; Sturm, Berger, and De Haan, 2005)). Furthermore, LICs tend to be repeat borrowers from the IMF, as they often face protracted balance of payments needs that cannot be addressed over the duration of a single program.

For these reasons, countries with a track record of frequent requests of IMF programs tend to have a higher probability of requesting an IMF program today. However, the interaction with the level of IMF resources should provide additional predictive power, as argued and shown in Lang (2021), Gehring and Lang (2020), and Krahnke (2023). During periods of relatively low IMF liquidity, countries with past program participation are likely

[6] We take the log of IMFLiquidity but we omit this fact in the rest of the paper to simplify notation.

to increase their probability of having an IMF-supported program compared to those who infrequently borrow from the IMF. The rationale provided in the literature is that the IMF, as any other financial institution, is likely to become more conservative in its lending when liquidity levels are relatively low, and vice-versa. Therefore, conditional on past use of IMF financing - which indicates potential future requests - the interaction of IMFProbability and IMFLiquidity should be a good predictor of program participation.

The IMFLiquidity variable we use in this study reflects available financing resources in the IMF's General Resources Accounts (GRA). All IMF members are eligible to borrow from these accounts. In contrast to non-LICs, LICs can also borrow from the IMF's Poverty Reduction and Growth Trust (PRGT) at concessional rates. The PRGT receives contributions from IMF members and the IMF itself. Its funds are not directly linked to the GRA, however in practice they are correlated.[7]

Using a measure of IMF Liquidity from the GRA instead of the PRGT reinforces the instrument's exogeneity assumption. Given that the amount of lending resources in the PRGT is donor based—and therefore donors may make additional contributions in times of need—variations in PRGT financing may not fully reflect real constraints on potential available financing. In contrast, we favor the use of IMF resources from the GRA which is largely financed by country's quotas which are subject to rules-based reviews at least every five years.

Within the IMF, an important principle guiding all lending operations is "equality of treatment" between members. Except for the borrowing rate, maturity, and a more tailored approach towards poverty reduction, IMF programs for LICs and non-LICs are largely similar (in terms of timing of negotiations, requiring the approval of the Board to disburse, and other institutional aspects). Similarities are such that some LICs can 'blend' and borrow from both the PRGT and GRA in the same program.

Variations in availability of resources in the GRA are largely driven by factors that are independent from idiosyncratic economic drivers in LICs. Key examples are quota reviews (more on this below) or large pre-determined repayments from individual high-access IMF programs (Krahnke, 2023). Therefore, the interaction between IMFProbability and IMFLiquidity (conditioning on IMFProbability) is likely to satisfy the exclusion restriction. We provide evidence that the exclusion restriction holds by controlling for other potential drivers of ODA in our baseline results (see Section 6). In Appendix B we show that this IV method does not suffer from spurious trends.

The second IV to address biases related to program size is

[7]The correlation between the uncommitted assets from the PRGT and the GRA is 0.57, for the years with overlapping data (2001-2019). The correlation between non-borrowed PRGT resources and available liquidity in the GRA is 0.7.

$$\frac{\text{AccessLimits}_{it}}{\text{GDP}_{it}} = \frac{\text{IMFQuota}_{it} \times \text{Limits}_{t}}{\text{GDP}_{it}} \tag{2}$$

where IMFQuota_{it} is the size of the IMF quota of country i in year t expressed in USD. Limits_t is the maximum amount of resources (in percent of quota) that a country can borrow in a single IMF arrangement without triggering exceptional access policies.[8] Thus, AccessLimits/GDP displays the *real* amount (in GDP terms) of lending that a requesting country can potentially borrow in a single arrangement.[9]

AccessLimits is an institutional nominal cap on the maximum amount of borrowing (in Special Drawing Rights) from the IMF available to each LIC. Therefore, it is a good predictor of the overall program size and its disbursements. The size of each program, together with the timing and policy requirements are negotiated and agreed at the time of the program request (see section 2). AccessLimits also satisfies the IV's exclusion restriction. These are reviewed by the IMF Board at least every five years. However, delays are common. The reviews of quotas often follow a specific formula for each country, and thus are uncorrelated with the short-run performance of macro-variables that are key in attracting ODA and overall capital flows (we provide empirical evidence on this in section 6).

Limits are also revised periodically, sometimes along with quotas, every few years to help ensure access to borrowing evolves broadly in line with demand based on macro developments such as the size of the economy and trade openness. These limits apply equally to all LICs (PRGT-eligible countries). Therefore, they are simpler and faster to adjust in periods of more demand for IMF financing (for example, in response to the COVID-19 pandemic) than quotas.

3.2 Econometric Specifications

We now move on to show the empirical estimation used to identify the catalytic impact of IMF lending on ODA flows. We first focus on a baseline estimation to capture the total catalytic effects (intensive plus extensive margin). Then we provide a decomposition for each margin. Finally, we discuss a decomposition of the analysis by donor and aid type and the possible non-linear effects of the catalytic effects.

[8] We use Limits specifically for borrowing from PRGT resources. These limits are more technically known as PRGT Cumulative Access Limits.

[9] From within IMF guidelines, the amount of lending a country eventually receives is generally driven by the balance of payment gap, the strength of the proposed policy actions and capacity to repay (International Monetary Fund, 2023a).

3.2.1 Total catalytic effects

Relying on the described IVs, we set a two-stage least squares (2SLS) specification. The second stage of our baseline is given by:

$$\log\left(\frac{\text{ODA}_{it}}{\text{GDP}_{it}}\right) = \beta_1 \frac{\widehat{\text{Disbursement}_{it}}}{\text{GDP}_{it}} + \beta_2 \text{IMFProbability}_{it} + \delta_i + \gamma_t + \varepsilon_{it}, \tag{3}$$

where ODA/GDP is the total flows of ODA (in percent of nominal GDP) that country i received in year t. Disbursement/GDP is the total amount of IMF disbursements measured in percent of nominal GDP borrower i received in year t. This may represent one or more individual disbursements received in year t. $\text{IMFProbability}_{it}$ is country i's rolling probability of requesting an IMF program based on past IMF programs. The specification includes country- δ_i and year- γ_t fixed effects. ε_{it} is the error term.[10] [11]

The coefficient β_1 measures the percentage change in the amount of ODA flows triggered by one pp change in annual disbursements. β_1 captures the total catalytic effect, the sum of the intensive and the extensive margins of participation in IMF programs. In other words, Disbursement/GDP can be seen as the interaction between participation in an IMF program and the average disbursement amount (as by definition no disbursement can occur outside an active program). Below we show how we can decompose these margins.

The first-stage regression is

$$\begin{aligned}\frac{\text{Disbursement}_{it}}{\text{GDP}_{it}} =& \alpha_1 \text{IMFProbability}_{it} \times \text{IMFLiquidity}_t + \alpha_2 \text{IMFProbability}_{it} \\ &+ \alpha_3 \frac{\text{AccessLimits}_{it}}{\text{GDP}_{it}} + \delta_i + \gamma_t + u_{it},\end{aligned} \tag{4}$$

where the interaction of IMFProbability and IMFLiquidity discussed in Section 3.1 is the main instrument to address edogeneity concerns regarding program participation. It is important to highlight that IMFProbability is included in the first and second stage, which means that the sole source of exogenous variation to identify program participation is the interaction term. According to our discussion, we would expect that past participation in IMF programs would lead to a higher probability of a new program request today ($\alpha_2 > 0$). But, when IMF resources are low (high), we expect to have a higher (lower) probability of an IMF program for more frequent users of IMF financing ($\alpha_1 < 0$).

In addition to addressing selection into programs, the first stage (4) also includes Ac-

[10] We take the log of ODA-to-GDP ratio due right-skewness of its distribution (see Figure 3), and to have normally distributed residuals.

[11] The ODA-to-GDP ratio may over-fluctuate given the decline of GDP in economic crises. Using alternative time composition of GDP, we find that the denominator does not drive our results.

cessLimits/GDP. This is our instrument to address biases related to program size, and thus, disbursement size. When the IMF increases its AccessLimits, countries have more capacity to borrow, in terms of GDP. We expect to observe $\alpha_3 > 0$.

While β_1 in (3) is of interest because it measures the percentage change in ODA following an increase in disbursements, an alternative measure to quantify the magnitude of the catalytic effects is to measure them in pp of GDP. To this aim, we compute the average marginal effects (AME) of the disbursements (at sample means) using the following formula:

$$\begin{aligned}\text{AME} =& \frac{\partial \mathbb{E}\left(\frac{\text{ODA}}{\text{GDP}} \middle| \frac{\text{Disbursement}}{\text{GDP}}\right)}{\partial \frac{\text{Disbursement}}{\text{GDP}}} \\ =& \frac{\partial \exp\left(\widehat{\beta_1 \overline{\frac{\text{Disbursement}_{it}}{\text{GDP}_{it}}}} + \widehat{\beta_2 \overline{\text{IMFProbability}_{it}}} + \widehat{\overline{\delta_i}} + \widehat{\overline{\gamma_t}}\right)}{\partial \widehat{\overline{\frac{\text{Disbursement}_{it}}{\text{GDP}_{it}}}}},\end{aligned} \tag{5}$$

where the numerator is the natural exponent of expression (3) with the estimated coefficients from the 2SLS. The variables with bars refer to sample means. Equation (5) allows us to compute how ODA in pp of GDP would change in response to a one pp increase in disbursement (in percent of GDP). In addition, it allows us to study how this magnitude has evolved over time by computing the AME at different time periods.

3.2.2 Catalytic effects decomposed by margin

The catalytic impact can be further decomposed into the magnitude of program participation (extensive margin) and disbursement amounts (intensive margin). The second stage is set up as:

$$\log\left(\frac{\text{ODA}_{it}}{\text{GDP}_{it}}\right) = \beta_1 \widehat{\frac{\text{Disbursement}_{it}}{\text{GDP}_{it}}} + \beta_2 \widehat{\text{IMFParticipation}}_{it} + \beta_3 \text{IMFProbability}_{it} + \delta_i + \gamma_t + \varepsilon_{it}, \tag{6}$$

where IMFParticipation is a dummy variable valued as one when the country is in an active program. Now β_1 quantifies the catalytic impact of disbursements on ODA while controlling for program participation. On the other hand, β_2 measures the catalytic effect of participation into programs conditional on how much is disbursed. To identify the catalytic effect of each margin, we will employ one instrument at a time. IMFParticipation is instrumented with the interaction of IMFProbability and IMFLiquidity, and

Disbursement/GDP instrumented with AccessLimits/GDP.

3.2.3 Decomposition of ODA and non-linear effects

Our analysis also expands to decompose the catalytic effects of IMF lending through different dimensions of ODA. We decompose the response of ODA flows by donors and type of assistance. In terms of donors, we distinguish three groups: i) traditional bilateral donors, ii) non-traditional bilateral donors and iii) multilateral organizations. Traditional donors refer to countries with OECD membership. See Appendix A for details. Given that multilateral organizations are the primary contributors of ODA in LICs, we further decompose this category into contributions from the European Union (EU), Regional Development Banks, the United Nations, the World Bank, and other multilateral organizations. Regarding aid types, we decompose ODA flows between concessional loans and grants.

Finally, we explore possible non-linearity in terms of the catalytic effects. For this we restrict our attention to a sample with active IMF programs. We set the following specification for the second stage of the 2SLS:

$$\log\left(\frac{\text{ODA}_{it}}{\text{GDP}_{it}}\right)\Bigg|_{\text{IMFProgram}=1} = \beta_1 \frac{\widehat{\text{Disbursement}}_{it}}{\text{GDP}_{it}} + \beta_2 \left(\frac{\widehat{\text{Disbursement}}_{it}}{\text{GDP}_{it}}\right)^2 + \delta_i + \gamma_t + \varepsilon_{it}. \quad (7)$$

We specifically aim to determine whether the size of the disbursement exhibits increasing, constant, or decreasing returns to scale by incorporating an additional quadratic term in our regression conditional on strictly positive disbursement years. Given this conditionality, we no longer need nor can use the interaction of IMFProbability and IMFLiquidity, and are left with a single instrument: AccessLimits/GDP.[12]

4 Data

Data for ODA is from the OECD Development Assistance Committee dataset (OECD, 2023). These are aid flows, in the form of grants, concessional loans with the purpose of promoting economic development and welfare. Loans must include a grant element of at least 25 percent calculated at a discount rate of 10 percent to qualify as ODA. For our dependent variable we utilize gross disbursements of ODA and follow Schiavone and Maurini (2023) and Gündüz and Crystallin (2018) in excluding certain flows from ODA. We exclude food and humanitarian aid, and technical cooperation as these are usually driven by event-

[12] To estimate a quadratic linear regression such as (7), which presents two endogenous variables and one IV, we follow the steps in Wooldridge (2010). We first run the first stage regression regressing Disbursements/GDP on AccessLimits/GDP. We then perform its linear projection. Then the squared of the projection, and use it as an instrument for (Disbursement/GDP)^2.

specific factors. In addition, we also subtract aid in the form of debt forgiveness and debt rescheduling's forgiven and rescheduled, as our main interest is new sources of financing.[13] Finally, we also subtract from ODA flows all loans and debt relief provided by the IMF.

Data on IMF disbursements is sourced from the Finance Department of the IMF. These data are accounting records of actual financial transactions between the IMF and its member countries and thereby present minimal measurement error. Our yearly measurement of disbursements is built by adding all disbursements to each country in a given calendar year. If the ongoing IMF program receives an augmentation, it is also recorded in the disbursement variable. With less than one percent of the sample composed of disbursements to blended borrowers the data includes very few blender country cases.[14] Disbursements are recorded in Special Drawing Rights (SDR). We transform them into USD at the recorded SDR/USD exchange rate. In terms of IMF program coverage, we only consider Upper Credit Tranche quality programs. These include the Stand-by and Extended Credit Facilities, and older versions of such programs. Our sample does not include disbursements from emergency financing programs.

The first IV employed in the econometric analysis is the interaction of IMFProbability and IMFLiquidity. IMFProbability is constructed as a 20-year rolling probability. It represents the percent of years in which country i participated in an IMF program in the 20 years preceding year t. Specifically, it is calculated as follows:

$$\text{IMFProbability}_{it} = \frac{1}{20} \sum_{\tau=t-19}^{t} \text{IMFParticipation}_{i\tau},$$

where

$$\text{IMFParticipation}_{it} = \begin{cases} 1 & \text{if country } i \text{ is in an IMF program in year } t \\ 0 & \text{otherwise.} \end{cases}$$

IMFLiquidity is a measure for the amount of resources that are the available for lending. As in Krahnke (2023), we use the IMF's forward commitment capacity (FCC) as a measure of IMF liquidity. The FCC reflects the annual available resources from its GRA.[15]

[13] Overall debt relief is not large compared to gross ODA flows, and our main results are not significantly affected by their exclusion.

[14] These are LICs that borrow from the IMF General Resources Accounts on top of the PRGT.

[15] The FCC measures the IMF's ability to make new financial commitments from the GRA to its members over the next 12 months. The FCC indicates how much the IMF has available for new lending from its regular financial resources and is adjusted downwards to account for resources already committed to members under existing IMF arrangements. A further downward adjustment is made to ensure that the Fund retains a prudential balance intended to safeguard the liquidity of creditors' claims and take account of the potential erosion of the IMF's resource base. Projected repayments from IMF borrowers over the

AccessLimits is the interaction between IMF quotas and cumulative access limits to the PRGT. Both variables are sourced from historic IMF records on country quotas and cumulative access limits to PRGT resources. The latter is a cap on borrowing amounts for each country, as a percent of quota, before triggering Exceptional Access policies. IMF programs under this policy often come with more stringent conditions and are subject to a higher level of scrutiny by the IMF's Executive Board, which could discourage such requests.

Additional data for the sensitivity analysis is collected from different sources. GDP growth and current account balance data are from the IMF World Economic Outlook indicators. For the degree of capital account openness we employ the Chinn-Ito index (Chinn and Ito, 2023). We also use a proxy for political stability. From the World Banks' Database on Political Institutions (World Bank, 2020), we employ the percentage of veto players (those with influence in political rulings) who drop from a government in a given year as a proxy for political stability.[16]

Our final data sample covers 63 LICs from 1990 to 2019. We focus on LICs that were eligible to receive concessional loans from the PRGT in 2019. We exclude countries that used to be PRGT eligible, but graduated from PRGT eligibility prior to 2019. More details on the sample coverage are provided in Appendix A.

5 Empirical Results

In this section we show the estimation results of the catalytic effects of IMF programs in LICs. We show first the total catalytic effects of disbursements and later decompose the results by the intensive and extensive margins. We then move on to analyze catalytic effects by donor and aid type. Finally we focus on possible non-linear effects of large disbursements.

5.1 Total Catalytic Effects

We begin our analysis by showing the OLS estimation results of regressions of ODA on disbursements as set up in specification (3). Table 1 presents the results. Column 1-3 show results for pooled OLS, and controlling for country and year fixed effects. The estimated coefficient exhibits a positive and statistically significant value, even in the absence of fixed effects. An increase of one pp in disbursements (in percent of GDP) is associated with a

next 12 months are then added to the total to derive the IMF's stock of usable resources.

[16] Veto players are defined as the president, largest party in the legislature, for a presidential system; and as the prime minister and the parties in the government coalition in a parliamentary system. The control variable captures the extent of turnover in any one year of a government's key decision makers. The variable is computed by dividing the number of exits between year t and $t+1$ by the total number of veto players in year t as specified in World Bank (2020). The control variable is a share with zero representing no exits and one representing the exit and replacement of all veto players (World Bank, 2020).

13.6 percent increase in ODA-to-GDP flows. In terms of pp of GDP (AME), this translates into additional ODA flows worth 0.69 pp of GDP. When we control for country and year fixed effects, the magnitude of the estimated coefficient becomes smaller. An increase of disbursements of one pp raises ODA flows by an average of 7 percent, or 0.35 pp of GDP.

Table 1: Total Catalytic Effects of IMF programs on ODA

	(1)	(2)	(3)	(4)	(5)	(6)
Second stage:						
	Dependent variable: log (ODA/GDP)					
	OLS	OLS	OLS	IV	IV	IV
Disbursement/GDP	0.136***	0.087***	0.070**	0.612***	0.528***	0.534***
	(0.046)	(0.033)	(0.029)	(0.204)	(0.161)	(0.158)
Marginal Effects (in pp of GDP)	0.69	0.44	0.35	3.01	2.67	2.70
R^2	0.05	0.05	0.03			
First stage:						
	Dependent variable: Disbursement/GDP					
IMFProbability				0.145***	-0.004***	0.009**
				(0.005)	(0.001)	(0.004)
IMFProbability × IMFLiquidity				-0.004***		-0.003***
				(0.001)		(0.001)
AccessLimit/GDP					0.095***	0.094***
					(0.026)	(0.026)
First stage R^2				0.14	0.18	0.18
Country FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
F-stat				14.24	13.16	8.23
J-stat (p-value)						0.63
Countries	63	63	63	63	63	63
Observations	1746	1746	1746	1746	1746	1746

Note: This table reports OLS and IV estimates of regressing log (ODA/GDP) on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. The IV regressions use IMFProbability × IMFLiquidity and AccessLimit/GDP are constructed based on (1) and (2) respectively. All regressions control for IMFProbability (not shown). The F-stat is Kleiberg-Paap Wald F-stat for weak identification. The J-stat is Hansen J-stat for overidentification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns 4-6 show the 2SLS results. Column 4 displays the results of instrumenting disbursements with *only* the interaction of IMFProbability and IMFLiquidity. The coefficient retains a positive sign but has a significantly larger magnitude compared to the OLS one. An increase in disbursements by one pp of GDP leads to a 61.2 percent rise in ODA-to-GDP flows. The AME quantifies that a 1 pp of GDP increase in disbursements leads to an additional increase of ODA of 3 pp of GDP. The Kleiberg-Paap Wald F-stat for weak identification is 14.2, well above the usual threshold of weak instrument (Stock and Yogo, 2005).

Column 5 replicates the same estimation, but using only AccessLimits/GDP as the instrument instead of the interaction of IMFProbability and IMFLiquidity. The estimated coefficient is highly significant and slightly smaller than the one in column 4. The 2SLS presents a F-stat of 13.16, which reflects that AccessLimits/GDP is not a weak instrument for disbursements.

Independently, columns 4 and 5 show that using different IVs to address biases from program participation and size is important to isolate the catalytic effects of IMF programs. In column 6 we employ both IVs at the same time to *simultaneously* control for these biases. The results show that a statistically significant coefficient of 0.53, implying that disbursements increase ODA-to-GDP ratio flows by 53 percent. In absolute terms, an increase in disbursements of 1 pp of GDP catalyzes ODA by 2.7 pp of GDP. Column 6 constitutes our most preferred specification for the rest of this study.

The first-stage results confirm the discussion in Section 3.1. The OLS coefficient of IMFProbability on disbursements is estimated to be positive in columns 4 and 6. These results imply that past users of IMF programs are more likely to request programs and receive disbursements today. While controlling for IMFProbability, column 4 displays the estimated coefficient of the interaction between IMFProbability and IMFLiquidity. It is negative and highly significant. As discussed, when IMF resources are low (high), it is more likely that more (less) frequent users of IMF programs request programs and receive disbursements.

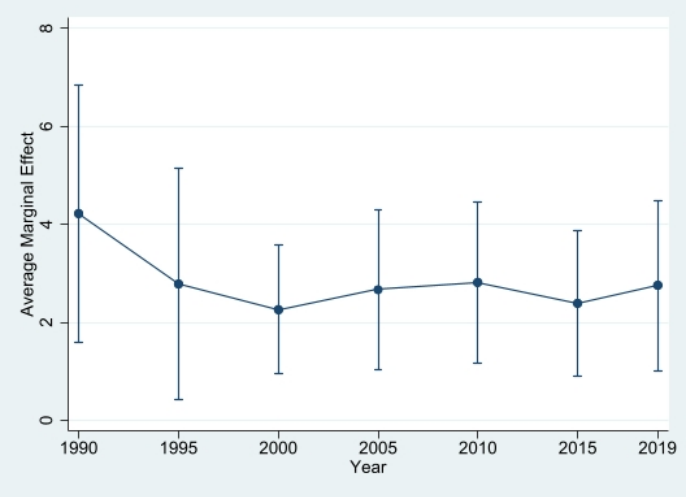
Column 5 shows the results of regressing disbursements on AccessLimits/GDP. As expected, the estimated coefficient is positive and significant. Larger lending capacity (in GDP terms) leads to larger programs and larger disbursements. One common source of variation in AccessLimits and IMFLiquidity is the review of IMF quotas, which simultaneously creates more resources and borrowing capacity (see Section 4). Even if there is a common source of variation in these instruments, column 6 shows that each IV is still significant in explaining disbursements when the other one is included in the specification. In addition, the p-value of Hansen J-stat for over-identification is 0.63, which indicates that each of our instruments is valid on its own right.[17][18]

The 2SLS effectively shows that there is a downward bias in the OLS results. The average amount of yearly disbursements (in percent of GDP) is 0.8, which implies that a program-requesting country could expect to receive additional ODA of 2.16 pp of GDP through each year under the program. This is in line with Gündüz and Crystallin (2018) who report that net ODA disbursements increase by 2.4 percent of GDP in countries with IMF programs. Schiavone and Maurini (2023) report that for each year under an IMF program there is a

[17] In other words, the null hypothesis that the over-identifying restrictions are valid cannot be rejected.

[18] These first-stage results are similar to those in Krahnke (2023), who run the same set of instruments but on a panel of emerging (non-LIC) countries.

Figure 5: Catalytic effect over time



Source: Authors' calculations based on OECD ODA database (OECD, 2023).

Note: This figure shows the average marginal effects of disbursements on ODA (as percent of GDP). 95 percent CIs are computed using the Delta method.

catalytic effect on ODA in LICs worth 1.6 pp of GDP.

Using the estimated coefficients from column 6 in Table 1, we now analyze how the catalytic effects evolved across time. For this, we compute the AME for different years. The results in Figure 5 demonstrates that the catalytic effects of IMF programs on ODA have remained broadly constant at around 2.7 pp of GDP in LICs during 1990-2019. There is a slightly larger catalytic impact for 1990, but not statistically different than in other years.

5.2 Decomposing the Catalytic Effects by the Intensive and Extensive Margins

We have shown that LICs in an active IMF program attracted larger ODA flows than what would otherwise have been the case. Next, we assess how relatively important program participation and lending size were in catalyzing ODA. In other words, did participation in an IMF program play a larger role than the actual lending amount received or was it the inverse? Fortunately, we have two IVs to aim at identifying each margin to answer this question.

Table 2 decomposes the IMF's catalytic effects by margins. We begin with a simple OLS regression in column 1 to set up a baseline for comparisons. The column presents the

OLS estimates of regressing ODA on disbursements (in percent of GDP) and country and year fixed effects.[19] Column 2 introduces a dummy variable, IMFParticipation, which is equal to one when a country is in an IMF-supported program. The coefficient of IMF-Participation captures the average catalytic effect of program participation, conditional on the average disbursed amount. Both coefficients for disbursements and participation are positive and statistically significant. As expected, the magnitude of the disbursement coefficient becomes slightly smaller.

Table 2: The Catalytic Effects by Margin

	(1)	(2)	(3)	(4)
Second stage:				
	Dependent variable: log (ODA/GDP)			
	OLS	OLS	IV	IV
Disbursement/GDP	0.070**	0.044**	0.539***	0.502***
	(0.029)	(0.021)	(0.177)	(0.184)
IMFParticipation		0.284***	-0.075	0.199
		(0.031)	(0.114)	(0.418)
R^2	0.03	0.08		
Marginal Effects (in pp of GDP) of Disbursement/GDP	0.35	0.22	2.72	2.53
Country and Year FE	Yes	Yes	Yes	Yes
IV: IMFProbability x IMFLiquidity			No	Yes
IV: AccessLimits/GDP			Yes	Yes
F-statistic			11.55	9.42
Countries	63	63	63	63
Observations	1746	1746	1746	1746

Note: This table reports OLS and IV estimates of regressing log (ODA/GDP) on Disbursement/GDP and IMFParticipation. The panel comprises annual data between 1990 and 2019 for 63 countries. IMFParticipation is instrumented with IMFProbability × IMFLiquidity (eq. 1), and Disbursement/GDP with AccessLimit/GDP (eq. 2), respectively. All regressions control for IMFProbability (not shown). First stage results are presented in Appendix C. The F-stat is Kleiberg-Paap Wald F-stat for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns 3 and 4 in Table 2 introduce our 2SLS approach to isolate the different margins. First stage results are presented in Appendix C. Column 3 uses AccessLimits/GDP as an instrument for disbursement amounts, while IMFParticipation is not instrumented. The results show that the coefficient on disbursements increases from 0.044 (OLS) to 0.539 (2SLS), which is essentially the same magnitude as in column 6 in Table 1.

In column 4 we replicate the 2SLS regression of column 3 but instrument IMFParticipation with the interaction of IMFProbability and IMFLiquidity. The magnitude of the coefficient

[19] This regression is the same as the one in column 3 in Table 1, which displays a positive and significant coefficient.

on IMF participation changes from negative to positive, but remains not statistically significant at the 10 percent level. On the other hand, the coefficient of disbursement declines compared to column 3, from 0.539 to 0.502. It remains highly significant. These results suggest that the amounts disbursed play a more important role in attracting ODA than the simple dummy of program participation. The first stage results of column 4 can be found in Appendix C.

5.3 Decomposing the Catalytic Effects by Donor and Aid Type

Next, we analyze the breakdown of the total catalytic effects of IMF programs on ODA by donor type and type of aid. Table 3 shows the catalytic effects of IMF programs on different donors using both IVs as in specification (3). Column 1 shows the catalytic effects on all donors.[20] Column 2 focuses on ODA provided only from traditional bilateral donors. The results suggest that a 1 pp increase in disbursements (in percent of GDP) leads to an average increase of ODA of 0.65 pp of GDP. Column 3 displays the catalytic effects on multilateral organizations. We observe the largest impact on these donors. Its coefficient shows that a 1 pp increase in IMF disbursements (in percent of GDP) raises ODA from multilateral organizations by 56 percent. In level terms, an increase in disbursements of one pp of GDP leads to an average increase of the ODA-to-GDP ratio in 1.4 pp.

Finally, column 4 shows the catalytic impact on non-traditional bilateral donors. The marginal impact is large, a one percent increase in disbursements leads to a 127 percent increase in ODA flows. However, this large marginal impact can be explained by the small ODA amounts usually contributed by these donors (as displayed in Figure 1). When we compute the AME, we find that one pp of disbursements (in percent of GDP) catalyzes only 0.05 GDP points of ODA.[21]

We further decompose the catalytic effects of IMF programs among multilateral organizations. Table 4 presents the catalytic effects of IMF programs on different multilaterals using the same specification (3). Column 2 presents the results for the catalytic effects on contributions by the European Union (EU). We find a positive and significant coefficient. A one pp increase in disbursements (in percent of GDP) increases ODA from the EU by 0.17 pp of GDP. Column 3 shows the impact on regional development banks. Surprisingly, we find no significant catalytic effects on these donors.[22] Column 4 shows the catalytic impact on the UN agencies. Overall, the IMF programs do catalyze a small amount of ODA from the UN at around 0.04 pp of GDP.

[20] These results are the same as in column 6 in Table 1

[21] We omitted analyzing contributions from private donors because they are not large enough to be representative.

[22] One reason why we may not observe catalytic effects is because RDBs usually provide more project financing than budget support, which may be less influenced by IMF financing.

Table 3: The catalytic effect by donor type

	(1) Total	(2) Traditional bilateral	(3) Multilateral Organizations	(4) Non-Traditional bilateral
Second stage:				
	Dependent variable: log (ODA/GDP)			
Disbursement/GDP	0.534***	0.331***	0.558***	1.271**
	(0.158)	(0.109)	(0.166)	(0.498)
Marginal Effect (in pp of GDP)	2.70	0.65	1.40	0.05
Country and Year FE	Yes	Yes	Yes	Yes
Countries	63	63	63	63
Observations	1746	1745	1745	1565

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP with a breakdown by donor type. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrbability and IMFLiquidity (1) and AccessLimits/GDP (2). All regressions control for IMFProbability in the second stage (not shown). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The catalytic impact of IMF lending on World Bank financing is presented in column 5. Both in percent changes and pp of GDP, we observe a large catalytic impact of IMF disbursements on the World Bank Group's ODA flows. On average, an increase in disbursements of 1 pp of GDP catalyzes ODA from the World Bank by 0.72 pp of GDP, increasing its ODA flows by 87 percent. Finally, column 6 studies the impact of IMF lending on other multilateral organizations not grouped in the above categories (see Appendix A). A positive and significant catalytic effect is found for this category, albeit with a small marginal effect.

Finally, we decompose ODA flows into concessional loans and grants. Table 5 displays the results. Column 1 shows the regression outcomes on total ODA flows, column 2 on concessional loans and column 3 on grants, respectively. Overall, we observe that a 1 pp increase in disbursements (in percent of GDP) increases concessional loans by 53.1 percent and grants by 37.2 percent. However, LICs receive more grants than concessional loans. When computing the AME, we observe that an increase in disbursements of 1 pp of GDP catalyzes concessional loans amounting to 0.66 pp of GDP, on average, and 1.17 pp of GDP in grants.

5.4 Decomposing the Catalytic Effects within IMF Programs

So far we have explored different dimensions of how IMF lending attracts ODA flows into a program country. In this subsection we restrict our attention by comparing the catalytic effects across active programs to analyze the relationship between the magnitude

Table 4: The catalytic effect by multilateral organizations

	(1) Total Multi-lateral	(2) EU	(3) Regional Dev. Banks	(4) UN	(5) World Bank Group	(6) Others
Second stage:						
	Dependent variable: log (ODA/GDP)					
Disbursement/GDP	0.558***	0.339**	0.162	0.227**	0.871***	0.231*
	(0.166)	(0.113)	(0.140)	(0.113)	(0.240)	(0.139)
Marginal Effects (in pp of GDP)	1.40	0.17	-	0.04	0.72	0.04
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	63	63	63	63	63	63
Observations	1745	1718	1418	1646	1594	1587

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP with a breakdown by multilateral organizations. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrbability and IMFLiquidity (1) and AccessLimits/GDP (2). All regressions control for IMFProbability in the second stage (not shown). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The catalytic effect by donor type

	(1) Total	(2) Concessional Loans	(3) Grants
Second stage:			
	Dependent variable: log (ODA/GDP)		
Disbursement/GDP	0.534***	0.531***	0.372***
	(0.158)	(0.192)	(0.116)
Marginal Effects (in pp of GDP)	2.70	0.66	1.17
Country and Year FE	Yes	Yes	Yes
Countries	63	62	63
Observations	1746	1693	1744

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP with a breakdown by aid type. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrbability and IMFLiquidity (1) and AccessLimits/GDP (2). All regressions control for IMFProbability in the second stage (not shown). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of disbursements and the amount catalyzed. To this end, we restrict our sample to countries that are actively receiving disbursements, following specification (7). Different from past regressions, we do not condition on IMFprobability (as it is not needed) and rely solely on AccessLimits/GDP as our instrument for amount of IMF lending.[23]

Table 6 reports the results. Columns 1 and 2 show the OLS and IV results of regressing ODA (in percent of GDP) flows on IMF disbursements, respectively, while controlling for country and year fixed effects. As previously discussed, OLS estimates suffer from a significant downward bias. The 2SLS coefficient shows that an increase in disbursements of 1 pp of GDP increases ODA flows (in percent of GDP) by 26 percent. In levels, this amounts to 1.8 pp of GDP. Larger disbursements (and programs) attract larger ODA flows, even when comparing across IMF programs.

Columns 3 and 4 test possible non-linearities of these catalytic effects. In column 3 we instrument Disbursement/GDP with AccessLimits/GDP, and control for Disbursement/GDP squared but do not instrument it. The estimated coefficient associated with disbursement squared reflects a negative and significant coefficient, although small compared to the linear term. In column 4 we replicate the results of column 3, but instrument disbursement and disbursement squared using AccessLimits/GDP following the steps in Wooldridge (2010).[24] The results confirm that there is a quadratic (inverted U-shape) effect of disbursements on ODA flows for LICs that receive IMF lending.

We find that larger programs catalyze more ODA. However, each additional SDR in access catalyzes less ODA than the previous one (decreasing marginal effects). There is a theoretical threshold beyond which additional disbursements could potentially reduce the catalytic effects of IMF lending to LICs in absolute terms. Nonetheless, based on the estimation results of Table 6, conservative estimates of such a threshold are around annual disbursements worth 12 pp of GDP, which is far from being reached in practice.[25]

6 Sensitivity Analysis

The previous section estimated the catalytic impact of IMF programs on ODA flows in LICs. In this section we conduct a sensitivity analysis to i) provide evidence that the exclusion restriction of the IVs hold and ii) to show that the estimated catalytic effects are robust to various modifications to the estimation sample, and inclusion of other potential

[23] Reduced-form results are presented in the Appendix C.

[24] We first run the first-stage regression regressing Disbursements/GDP on AccessLimits/GDP. We then perform its linear projection. Then we square such projection and use it as an instrument for (Disbursement/GDP)^2. See Section 3.2 for details.

[25] In Appendix D we further explore whether this quadratic effect is increasing in the stock of public debt. We do not find evidence that the diminishing returns to catalytic effects are more pronounced when debt levels are higher.

Table 6: The catalytic effect and disbursement size

	(1)	(2)	(3)	(4)
Second stage:				
	Dependent variable: log (ODA/GDP)			
	OLS	IV	OLS	IV
Disbursement/GDP	0.0272**	0.257***	0.101***	0.662***
	(0.013)	(0.097)	(0.032)	(0.135)
(Disbursement/GDP)^2			-0.003***	-0.026***
			(0.001)	(0.007)
Marginal Effects (in pp of GDP)	0.19	1.80	Non-Linear	Non-Linear
Country and Year FE	Yes	Yes	Yes	Yes
F-stat		7.57		7.28
Countries	51	51	51	51
Observations	702	702	702	702

Note: This table reports OLS and IV estimates of regressing log (ODA/GDP) on Disbursement/GDP and (Disbursement/GDP)^2 conditional on a sample of countries receiving disbursements. The panel comprises annual data between 1990 and 2019 for 51 countries. Disbursement/GDP is instrumented with AccessLimit/GDP (eq. 2) . The F-stat is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

drivers of ODA, such as debt relief.

We begin by showing that the IVs we use to identify the causal impact of IMF programs on ODA are not correlated with other determinants of ODA flows (as discussed in Section 3.1). In other words, we provide evidence that the exclusion restriction of our IVs holds. To this aim, we estimate our baseline specification (3) and include different control variables that are usual determinants of ODA flows (Rabehajaina, Gueyie, and Sedzro, 2023).

Table 7 presents the results. Column 1 shows the baseline results of regressing ODA flows on IMF disbursements (in percent of GDP). Column 2 includes real GDP growth as a control. One could expect that low and negative growth could be a good predictors of ODA and IMF program requests. The estimated coefficient for Disbursement/GDP remains unchanged. In column 3 we include current account balance (which is simultaneously a predictor of ODA flows and IMF programs) and find that our estimated coefficient still remains broadly unchanged at 0.534.

In column 4 we control for capital account openness (Chinn and Ito, 2023). Countries that have more open capital account are expected to attract more capital flows (ODA among them). We find support for this claim but controlling for capital account openness does not significantly change the instrumented coefficient of disbursements. In column 5 we include a proxy for political stability and good governance. Countries with robust institutional environments and better governance are more likely to attract more ODA (Dabla-Norris,

Minoiu, and Zanna, 2010). Our estimated coefficient on the response of ODA flows to IMF disbursements (column 1) remains significantly constant when including each of these controls separately, and even all at the same time (column 6). These results support our selection for IVs that are largely based on rules-based institutional changes at the IMF and that do not depend on the current macroeconomic performance of LICs.

Table 7: The catalytic effects of IMF programs and other determinants of ODA

	(1)	(2)	(3)	(4)	(5)	(6)
Second stage:						
	Dependent variable: log (ODA/GDP)					
Disbursement/GDP	0.534***	0.537***	0.534***	0.601***	0.501***	0.569***
	(0.158)	(0.175)	(0.159)	(0.155)	(0.149)	(0.157)
Real GDP growth		0.000				0.002
		(0.005)				(0.002)
Current Account balance			0.000			-0.001
			(0.002)			(0.005)
Capital Account Openness (Chinn and Ito index)				0.163*		0.142
				(0.085)		(0.100)
Political Stability					-0.033	-0.006
					(0.052)	(0.058)
Marginal Effects (in pp of GDP)	2.70	2.70	2.99	2.67	2.51	2.75
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	8.23	7.52	8.19	9.72	7.93	10.72
Countries	63	63	63	63	59	59
Observations	1746	1671	1746	1675	1615	1481

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrbability and IMFLiquidity (1) and AccessLimits/GDP (2). All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistic for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we also conducted a sensitivity analysis on variations in the estimation sample, e.g., we excluded countries by region and export structure, and used the lag of GDP to assess the influence of the denominator in the estimated results. These results are presented in Appendix D.

7 Conclusions

In this study, we examine the catalytic impact of IMF programs on ODA for LICs and answer the following questions: How large is the catalytic effect of IMF programs on ODA? How has it evolved over the past decades? Which donors contribute the most and through which aid type (grants vs concessional loans)? Does the size of IMF disbursements matter for the amounts of catalyzed financial assistance?

To answer these questions, we rely on the use of IVs to address the challenges of selection bias stemming from participation into IMF programs and program size. Unlike previous studies that relied on *selection on observables*, our paper employs two distinct IVs aimed at addressing each of these biases.

Our findings highlight a significant catalytic impact of IMF lending on ODA in LICs. We quantify that an increase in IMF disbursements of 1 pp of GDP catalyzes additional ODA flows worth 2.7 pp of GDP. Given the typical size of IMF disbursements, this implies that, on average, a LIC engaged in an IMF-supported program can expect to receive an additional 2.2 pp of GDP annually in ODA.

Multilateral organizations, with the World Bank and the European Union at the forefront, emerge as the primary contributors to the catalytic effects, together with traditional bilateral donors. Additionally, our analysis indicates that the catalytic effect of IMF programs pertains more to grants than to concessional loans, emphasizing the importance of aid modalities in shaping the impact of IMF programs on ODA. With LICs' external financing needs exacerbated by a series of global shocks amid tighter market conditions, the catalytic impact of IMF lending has regained importance in closing financing gaps and cushioning adjustment needs.

Furthermore, our exploration into the size of IMF disbursements reveals that larger amounts catalyze more substantial ODA flows. While program participation remains a relevant factor, the amount of lending is more statistically relevant, suggesting that the sheer magnitude of IMF support plays a crucial role in attracting additional external financing. Finally, we also document that the catalytic effects are declining in the size of the IMF programs.

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A Appendix: Details on Sample Coverage

A.1 Key variables and sources of data

Table A1: Main variables: coverage and sources of data

Variable	Coverage	Source
ODA	1990-2019	OECD DAC database
Disbursements	1990-2019	IMF Financial Data Query Tool
PRGTParticipation	1990-2019	IMF Financial Data Query Tool
IMFProbability	1971-2019	IMF Annual Financial Reports
IMFLiquidity (FCC)	1990-2019	IMF
Quotas	1990-2019	IMF Financial Data Query Tool
Cumulative Access Limits to the PRGT	1990-2019	IMF
Nominal GDP	1990-2019	WB World Development Indicators

A.2 List of 63 LICs in the baseline sample

Afghanistan, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Djibouti, Dominica, Ethiopia, The Gambia, Ghana, Grenada, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Kenya, Kyrgyz Republic, Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Maldives, Mali, Mauritania, Republic of Moldova, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Papua New Guinea, Rwanda, Samoa, Sao Tome & Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, St. Lucia, St. Vincent and the Grenadines, Sudan, Republic of Tajikistan, Tanzania, Togo, Tonga, Uganda, Republic of Uzbekistan, Vanuatu, Republic of Yemen, Zambia, Zimbabwe.

A.3 Composition of donors

Traditional bilateral donors: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom and the United States.

Non-Traditional bilateral donors: Azerbaijan, Bulgaria, Chinese Taipei, Croatia, Cyprus, Estonia, Israel, Kazakhstan, Kuwait, Latvia, Liechtenstein, Lithuania, Malta, Monaco, Qatar, Romania, Russian Federation, Saudi Arabia, Thailand, Timor-Leste, Türkiye and United Arab Emirates.

Multilateral Organizations:

- **EU Institutions**

- **Regional Development Banks:** African Development Bank (AfDB), Asian Development Bank (AsDB), Inter-American Development Bank (IDB), Asian Infrastructure Investment Bank (AIIB), Arab Bank for Economic Development in Africa (BADEA), Central American Bank for Economic Integration (CABEI), Caribbean Development Bank (CarDB), Council of Europe Development Bank (CEB), European Bank for Reconstruction and Development (EBRD), Islamic Development Bank (IsDB), North American Development Bank (NADB).

- **United Nations:** Central Emergency Response Fund (CERF), Food and Agriculture Organisation (FAO), IFAD, International Atomic Energy Agency (IAEA), International Labour Organisation (ILO), Joint Sustainable Development GOals Fund (Joint SDG Fund), UN Capital Development Fund (UNCDF), UN Institute for Disarmament Research (UNIDIR), UN Peacebuilding Fund (UNPBF), UN Women, UNAIDS, UNDP, UNECE, UNEP, UNFPA, UNHCR, UNICEF, United Nations Conference on Trade and Development (UNCTAD), United Nations Industrial Development Organization (UNIDO), UNRWA, UNTA, WFP, WHO-Strategic Preparedness and Response Plan (SPRP), World Health Organisation (WHO), World Tourism Organisation (UNWTO), WTO - International Trade Centre (ITC).

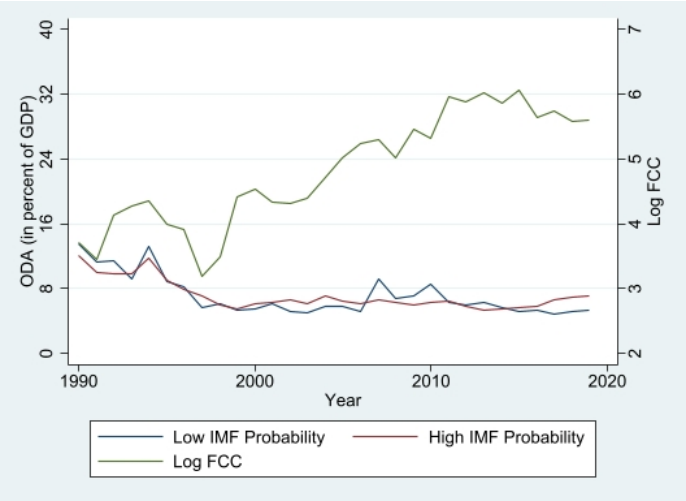
- **World Bank Group:** International Bank for Reconstruction and Development (IBRD), International Development Association (IDA) and the International Finance Corporation (IFC).

- **Other Multilateral:** Adaptation Fund, Arab Fund (AFESD), Asian Forest Cooperation Organisation (AFoCO), Center of Excellence in Finance (CEF), CGIAR, Climate Investment Funds (CIF), Global Alliance for Vaccines and Immunization (GAVI), Global Environment Facility (GEF), Global Fund, Global Green Growth Institute (GGGI), Green Climate Fund (GCF), International Centre for Genetic Engineering and Biotechnology (ICGEB), International Commission on Missing Persons (ICMP), Montreal Protocol, Nordic Development Fund (NDF), OPEC Fund for International Development (OPEC Fund), OSCE, World Organisation for Animal Health (WOAH).

B Appendix: Checking for Spurious Correlations in the Identification Strategy

One potential concern with the first IV is that it may be suffer from spurious trends, as discussed in Christian and Barrett (2017). This would be the case if countries with higher IMFprobability receive proportionally more ODA as IMF liquidity increases over time. We show that this is not the case by separating LICs into a group with a low probability of IMF program (below 50 percentile of IMFProbability), and another one with high probability (above 50 percentile of IMFProbability). Figure A1 shows these trends. There is no apparent overlap in long-run trends in any of these groups with the IMF liquidity time series. Using other percentiles yields similar results. This evidence suggest the absence of spurious trends in our IV approach.

Figure A1: The IMF's liquidity and trends in ODA



Note: The blue line plots the mean of ODA for countries that have a low probability of participation in IMF programs in the most recent 20-year period (below 50th percentile). The red line plots the mean of ODA for countries that have a high probability of participation in IMF programs in the most recent 20-year period (above 50th percentile). The green line plots the logarithm of the FCC variable. Source: Authors' calculations based on OECD ODA database (OECD, 2023).

C Appendix: Empirical Results (Additional Tables)

C.1 First Stage Regressions of Table 2

Table A2: First Stage Results of Table 2

	(1)	(2)
	Dependent variable:	
	Disbursement/GDP	IMFParticipation
IMFProbability	0.009**	0.012***
	(0.004)	(0.002)
IMFProbability × IMFLiquidity	-0.004***	-0.002***
	(0.001)	(0.000)
AccessLimit/GDP	0.094***	0.012***
	(0.026)	(0.004)
R^2	0.18	0.41
Country FE	Yes	Yes
Year FE	Yes	Yes
Countries	63	63
Observations	1746	1746

Note: This table reports the first stage (OLS) results of Table 2. The panel comprises annual data between 1990 and 2019 for 63 countries. IMFProbability × IMFLiquidity and AccessLimit/GDP are constructed based on (1) and (2) respectively. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: *Reduced form* evidence of catalytic effects and program size (based on Table 6)

	(1)	(2)
	Dependent variable: log (ODA/GDP)	
AccessLimit/GDP	0.0425***	0.0913***
	(0.00956)	(0.0102)
$(\text{AccessLimit/GDP})^2$		-0.000949***
		(0.000177)
Country FE	Yes	Yes
Year FE	Yes	Yes
Countries	51	51
Observations	702	702

Note: This table reports the reduced-form (OLS) results of Table 6 by regressing log (ODA/GDP) (for observations with positive disbursements) on the IVs AccessLimit/GDP and $(\text{AccessLimit/GDP})^2$. The panel comprises annual data between 1990 and 2019 for 63 countries. AccessLimit/GDP is constructed based on (2). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Appendix: Sensitivity Analysis (Additional Results)

Here we extend our sensitivity analysis to show that our main results are not sensitive to the exclusion of potential events and variations in the country sample.

D.1 Special events

Table A4: The catalytic effects of IMF programs excluding regions with sample variations

	(1) Baseline	(2) Excluding GFC years	(3) Excluding precautionary programs	(4) Controlling for IMF debt relief
Second stage:				
	Dependent variable: log (ODA/GDP)			
Disbursement/GDP	0.534***	0.510***	0.533***	0.523***
	(0.158)	(0.149)	(0.159)	(0.155)
IMF Debt Relief/GDP				0.039***
				(0.011)
Marginal Effects (in pp of GDP)	2.70	2.59	2.70	2.64
Country and Year FE	Yes	Yes	Yes	Yes
F-stat	8.23	8.25	8.02	8.15
Countries	63	63	63	63
Observations	1746	1563	1738	1746

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. The instruments IMFProbability × IMFLiquidity and AccessLimit/GDP are constructed based on Equations (1) and (2) respectively. All regressions control for IMFProbability in the second stage (not shown). The F-statistic is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 1 in Table A4 shows our baseline results as a benchmark for comparisons. These are the same results as in column 6 in Table 1. In column 2 we show that these baseline results are robust to a series of modifications to the sample. In column 2 we exclude the years following the Global Financial Crisis (2008-2010 period). During this period, there was a large decline in global demand and a spike in uncertainty that challenged LICs' capacity to attract capital inflows. We find that the magnitude of the estimated catalytic effects is not significantly driven by the global developments in this period. In Column 3, we exclude a few cases where IMF programs were requested for precautionary reasons. The estimated coefficient does not change much. In column 4 we control for the amount of IMF-provided debt relief. Through the Heavily Indebted Poor Countries (HIPC) Initiative, which began in 1996, the IMF provided debt relief to several LICs. This relief was typically granted in tandem with IMF-supported programs. We control for the amount of debt relief

provided per year (not-instrumented) and find almost no changes to our baseline results.

D.2 Regional and export-type heterogeneity

Table A5: The catalytic effects of IMF programs excluding regions

Excluding countries in	(1) None	(2) Europe and Central Asia	(3) Latin America and Caribbean	(4) Middle East North Africa	(5) South Asia	(6) Sub-Saharan Africa
Second stage:						
	Dependent variable: log (ODA/GDP)					
Disbursement/GDP	0.534***	0.544***	1.205*	0.530***	0.554***	0.338***
	(0.158)	(0.166)	(0.658)	(0.158)	(0.165)	(0.095)
Marginal Effects (in pp of GDP)	2.70	2.83	6.46	2.68	2.86	1.32
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	8.23	8.77	3.90	8.05	7.63	11.66
Countries	63	59	55	61	59	28
Observations	1746	1654	1510	1687	1638	719

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrbability and IMFLiquidity (1) and AccessLimits/GDP (2). All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistic for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Europe and Central Asia (ECA):** Kyrgyz Republic, Republic of Moldova, Republic of Tajikistan, Republic of Uzbekistan. **Latin America and Caribbean (LAC):** Dominica, Grenada, Guyana, Haiti, Honduras, Nicaragua, St. Lucia, St. Vincent and the Grenadines. **Middle East North Africa (MNA):** Djibouti, Republic of Yemen. **South Asia (SAR):** Afghanistan, Bangladesh, Maldives, Nepal. **Sub-Saharan Africa (SSA):** Benin, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Ethiopia, The Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Rwanda, Sao Tome & Principe, Senegal, Sierra Leone, Somalia, South Sudan, Sudan, Tanzania, Togo, Uganda, Zambia, Zimbabwe. **East Asia and Pacific (EAP):** Cambodia, Chad, Comoros, Lao People's Democratic Republic, Myanmar, Papua New Guinea, Samoa, Solomon Islands, Tonga, Vanuatu.

We also show that our results are robust to variations in the country composition. First, we group LICs in five regions: Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, Asia and Pacific, and sub-Saharan Africa. Then we run our baseline regression and remove one region at a time. In Table A5 we find that our results are not driven by one particular region. More than half of our main sample is composed by sub-Saharan Africa countries. When we remove these countries from the sample the magnitude of the catalytic effect on ODA declines by half from 2.7 to 1.3 pp of GDP. This result implies that catalytic effects of IMF programs in sub-Saharan African countries is larger than the average 2.7 pp of GDP for this group of countries.

Table A6: The catalytic effects of IMF programs excluding countries based on their main source of exports

Excluding countries with main source of export earnings from	(1) None	(2) Fuel	(3) Manuf.	(4) Primary Products	(5) Services	(6) Diversified Products
Second stage:						
	Dependent variable: log (ODA/GDP)					
Disbursement/GDP	0.534***	1.012*	0.523***	0.442***	0.498***	0.459***
	(0.158)	(0.546)	(0.155)	(0.125)	(0.156)	(0.137)
Marginal Effects (in pp of GDP)	2.70	5.30	2.75	1.99	2.40	2.45
Country and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	8.23	5.34	8.14	18.65	6.13	6.86
Countries	63	58	58	42	45	49
Observations	1746	1628	1601	1178	1220	1357

Note: This table reports IV estimates of regressing log (ODA/GDP) on Disbursement/GDP. The panel comprises annual data between 1990 and 2019 for 63 countries. Disbursement/GDP is instrumented using the interaction of IMFPrbability and IMFLiquidity (1) and AccessLimits/GDP (2). All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistic for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Main source of export based on WEO definition: **Fuel:** Chad, Republic of Congo, Guyana, South Sudan, Republic of Yemen. **Manufactures:** Bangladesh, Cambodia, Cote d'Ivoire, Haiti, Lesotho. **Primary Products (Excluding Fuel):** Afghanistan, Benin, Burkina Faso, Burundi, Central African Republic, Democratic Republic of Congo, Ghana, Guinea, Guinea-Bissau, Liberia, Malawi, Mali, Mauritania, Papua New Guinea, Sierra Leone, Solomon Islands, Somalia, Sudan, Republic of Tajikistan, Zambia, Zimbabwe. **Services:** Cape Verde, Comoros, Djibouti, Dominica, Ethiopia, The Gambia, Grenada, Kyrgyz Republic, Maldives, Nepal, Niger, Rwanda, Samoa, Sao Tome & Principe, St. Lucia, St. Vincent and the Grenadines, Tonga, Vanuatu. **Diversified Products:** Cameroon, Honduras, Kenya, Lao People's Democratic Republic, Madagascar, Republic of Moldova, Mozambique, Myanmar, Nicaragua, Senegal, Tanzania, Togo, Uganda, Republic of Uzbekistan.

We also conduct a sensitivity analysis to show that our results are robust to variations in the main source of export earnings. First, we separate LICs into five groups by source of export earnings: fuel, manufactures, primary products (excluding fuel), services, and diversified products. Then, we run our baseline regression and remove one group at a time. In Table A6 we find that our results are not driven by any particular group.

D.3 GDP denominator

One concern regarding ODA in percent of GDP, is that countries are more likely to request an IMF program when GDP contracts. We show that our results are not especially sensitive to its denominator. In Table A7, we re-estimate the regressions in Table 1 using a one-year lag of GDP in all our variables measured in GDP terms. Column 1-3 show results for pooled OLS, and controlling for country and year fixed effects, while Columns 4-6 show the 2SLS results. The estimated coefficients still exhibit are positive and statistically significant. The Kleiberg-Paap Wald F-stat for weak identification is still well above the usual threshold of weak instrument (Stock and Yogo, 2005). In Column 6, our most preferred specification, an increase of one pp in disbursements (in percent of GDP in time (t-1)) is associated with an additional ODA flows worth 2.58 pp of GDP in time (t-1) instead of the 2.7 in Column 6 of Table 1.

Table A7: Total catalytic effects using one-year lag of GDP

	(1)	(2)	(3)	(4)	(5)	(6)
Second stage:						
	Dependent variable: log (ODA/GDP(t-1))					
	OLS	OLS	OLS	IV	IV	IV
Disbursement/GDP(t-1)	0.122***	0.074***	0.061**	0.701***	0.471***	0.487***
	(0.040)	(0.026)	(0.026)	(0.263)	(0.170)	(0.171)
Marginal Effects (in pp of GDP(t-1))	0.64	0.39	0.32	3.71	2.49	2.58
R^2	0.05	0.05	0.02			
First stage:						
	Dependent variable: Disbursement/GDP					
IMFProbability				0.011**	-0.005***	0.007
				(0.006)	(0.002)	(0.005)
IMFProbability × IMFLiquidity				-0.003***		-0.002***
				(0.001)		(0.001)
AccessLimit/GDP(t-1)					0.086***	0.084***
					(0.027)	(0.027)
Country FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
F-stat				10.11	10.14	6.03
Countries	63	63	63	63	63	63
Observations	1682	1682	1682	1682	1682	1682

D.4 Intensive margin and government debt

In this subsection we investigate if the catalytic effect of disbursement size, as illustrated in Table 6, is affected by sovereign debt levels. We would like to know if the quadratic term is affected when controlling by government debt. The rationale being that large debt pressures (here proxied by debt to GDP ratio) may encourage more ODA when debt pressures are high to aid struggling LICs. Conversely, high levels of debt could also deter ODA after Fund lending comes in due to the higher likelihood of a potential restructuring case.

One empirical challenge here is that Table 6 employed a double-instrument approach to IMF disbursements. Adding a further interaction may pose econometric challenges. To simplify, we decided to apply the "reduced-form" approach and use the instrument AccessLimits/GDP as the proxy for disbursements. Table A8 shows the ordinary least squares (OLS) outcomes with government debt included as a control variable. The initial two columns reaffirm the baseline reduced-form outcomes, where there is a quadratic effect of access limits on ODA. The introduction of government debt as a control variable in Column 3, and the inclusion of an interaction term between Debt/GDP and the square of AccessLimit/GDP in Column 4, do not alter the overarching conclusion: program size is positively and significantly related to the outcomes, whereas the square of program size has a negative and significant causal effect. Nonetheless, we observe that the interaction between AccessLimits/GDP squared and government debt is positive and significant. This means that the so call decreasing catalytic effects become "less concave" when debt levels are high. We replicated the analysis on ODA from bilateral and multilateral creditors separately (not shown). Both display the similar results as in column 4.

Further evidence is presented in Table A9, where we replicate Table 6 by separating the data sample into two categories based on the annual median Debt-to-GDP ratio. Columns 1 and 2 revisit the primary findings from Table 6. Subsequent analyses in Columns 3 and 4 apply the regression model from Column 2 separately to the groups characterized by high and low Debt-to-GDP ratios. For both divisions, we observe that the coefficients associated with program size remain positively significant, and those related to the squared program size are negatively significant.

Table A8: *Reduced form* evidence of catalytic effects and program size controlling government debt

	(1)	(2)	(3)	(4)
	Dependent variable: log (ODA/GDP)			
AccessLimit/GDP	0.0425***	0.0913***	0.0854***	0.110***
	(0.00956)	(0.0102)	(0.0105)	(0.0163)
$(\text{AccessLimit/GDP})^2$		-0.000949***	-0.000921***	-0.00201***
		(0.000177)	(0.000179)	(0.000546)
Debt/GDP			0.000991*	0.000222
			(0.000512)	(0.000671)
Debt/GDP $\times$ $(\text{AccessLimit/GDP})^2$				0.00000259**
				(0.00000115)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Countries	51	51	51	51
Observations	702	702	681	681

Note: This table reports the reduced-form (OLS) results of Table 6 by regressing log (ODA/GDP) (for observations with positive disbursements) on the IVs AccessLimit/GDP and $(\text{AccessLimit/GDP})^2$ controlling government debt. The panel comprises annual data between 1990 and 2019 for 51 countries. AccessLimit/GDP is constructed based on (2). Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: The catalytic effects and program size by high and low government debt levels

	(1) Baseline	(2) Baseline	(3) Low Debt/GDP	(4) High Debt/GDP
Second stage:				
	Dependent variable: log (ODA/GDP)			
	OLS	IV	IV	IV
Disbursement/GDP	0.101***	0.662***	1.153**	0.758**
	(0.0318)	(0.135)	(0.524)	(0.343)
(Disbursement/GDP)^2	-0.003***	-0.026***	-0.033**	-0.062**
	(0.001)	(0.007)	(0.015)	(0.0256)
Country and Year FE	Yes	Yes	Yes	Yes
F-stat		7.28	3.14	2.55
Countries	51	51	42	40
Observations	702	702	346	351

Note: This table reports OLS and IV estimates of regressing log (ODA/GDP) on Disbursement/GDP and (Disbursement/GDP)^2 conditional on a sample of countries receiving disbursements. The panel comprises annual data between 1990 and 2019 for 51 countries. Disbursement/GDP is instrumented with AccessLimit/GDP (Equation (2)). The cutoff between low and high Debt/GDP in Columns (3) and (4) is the median Debt/GDP across all countries in each year. The sum of the number of countries in low and high Debt/GDP groups is larger than the total number of countries because a country can switch between these two groups over time. All regressions control for IMFProbability in the second stage (not shown). The F-stat is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$..

PUBLICATIONS

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