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Determinants of Pre-Pandemic Demand for the IMF's Concessional Financing

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Abstract

This study focuses on identifying the main factors that influenced country-specific and aggregate demand for IMF concessional financing between 1986 and 2018 and makes within-period and out-of-period forecasts. We find that the external debt level, inflation, and real effective exchange rate are the main economic variables influencing concessional borrowing for most eligible countries. Finally, our approach is able to provide quite accurate country-level and aggregate forecasts for historical financing events prior to the COVID-19 pandemic.

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TABLE OF CONTENTS

FIGURES

TABLES

APPENDICES

I. INTRODUCTION

The IMF can provide financial assistance for eligible low-income countries in the form of concessional loans. Such assistance is provided through the facilities of the Poverty Reduction and Growth Trust (PRGT), which assists eligible countries in achieving and maintaining a stable and sustainable macroeconomic position consistent with strong and durable poverty reduction and growth (IMF, 2018). Given increased demand for IMF concessional financing in recent years prior to the COVID-19 pandemic and the relative scarcity of these resources, it is important to understand the factors behind the demand for concessional financing and to forecast its demand. This analysis is based on pre-pandemic factors.[2]

Several papers have studied the determinants of IMF's financing.[3] The literature has examined the links between domestic conditions[4] and the IMF's financing for a typical developing country[5]. However, it has not focused on analyzing country-specific factors that influence concessional borrowing and using the country-specific factors to predict the likelihood of the country's future concessional financing demand. Moreover, the literature does not seem to have sought to use these country-specific factors to predict aggregate demand for concessional financing. This paper seeks to fill these gaps. Specifically, the paper makes three contributions to the literature: first, it applies a factor-augmented probit model to find the set of variables that are statistically accurate in replicating the factors that have influenced concessional borrowing for a PRGT-eligible country; second, it uses the identified set of factors to predict the country's future demand for concessional financing; and third, it uses the country-specific prediction and a balanced statistical approach to estimate aggregate demand for the currently PRGT-eligible countries. In summary, this paper aims to address the following questions: (1) What are the main country-specific factors of a country's demand for concessional financing? (2) What is the probability that the country would request concessional financing in the future? (3) How much is the predicted annual aggregate demand for concessional financing?

The paper has three main findings. First, we found that the main country-specific factors for demand vary among PRGT-eligible countries. The external debt level, inflation, and real

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[2] This study started in summer 2019 and was completed before the COVID-19 pandemic that started in early 2020. Its findings and conclusions on factors affecting IMF concessional demand are based on historical data as of end-2018 (i.e., on pre-pandemic factors). The COVID-19 pandemic is unprecedented, hence potentially affecting the paper's results which are relevant under non-pandemic conditions. It would be too early to include the on-going pandemic as a global factor behind the demand for PRGT resources in our study.

[3] See Bird and Orme, 1981; Cornelius, 1987; Conway, 1994; Knight and Santaella, 1997; Bird and Rowlands, 2009; and Gündüz, 2009.

[4] Some of the variables analyzed include the share of current account balance in total trade, inflation, imports, reserves, and GDP growth.

[5] We use the phrase "developing countries" and "low-income countries" interchangeably.

effective exchange rate are the most commonly observed country-specific conditions among countries requesting concessional financing. Second, while we find that global factors do not seem to improve the model's prediction accuracy, a possible explanation may be that the informative power of these global variables may already be captured in some of the domestic factors. Finally, the estimation model has significant capability in forecasting the demand for concessional financing at country and aggregate levels.

The rest of the paper is structured as follows. Section II summarizes the literature. Section III illustrates IMF financing arrangement statistics and stylized facts of key factors of demand for concessional financing prior to an IMF financing arrangement. Section IV describes the empirical model and data. Section V discusses the empirical results and robustness checks, including in- and out-of-sample forecast performance. Section VI concludes and provides policy implications.

II. Literature Review

Several studies have attempted to identify factors of a developing country's demand for IMF financing. Earlier studies, such as Bird and Orme (1981), using cross-section OLS, find that in both 1976 and 1977 the current account balance, inflation, GNP per capita, imports, reserves, and eurocurrency credit are significantly linked to developing countries' higher demand for IMF financing. Using pooled OLS, Cornelius (1987) shows that Sub-Saharan African countries' demand during 1975-1977 for IMF loans is associated with countries' inflation, GNP per capita, imports, foreign debt service, and external borrowing from international capital markets. However, his estimates also indicate that imports are the only significant variable determining demand during the period 1981-1983.

Later studies have used advanced panel data methods and found a significant link between domestic factors and IMF financing. Joyce (1992) examines the economic profile of countries entering into IMF stabilization programs. Using logit panel regression with annual data for 45 developing countries, he finds that growth in a central bank's holdings of domestic assets, government expenditure, the current account balance, reserves, and GDP per capita are important indicators linked to IMF financing. One of the two objectives of Conway (1994) is to analyze countries' motivation for requesting IMF financing. His panel data probit estimates for 74 developing countries from 1976 to 1986 show that past economic performance (e.g., lagged economic growth, lagged inflation or lagged domestic investment ratio), contemporaneous external influences (e.g., economic performance of other countries with IMF financing arrangement), and sluggish adjustment in these countries drive them to apply for an IMF financial arrangement. Knight and Santaella (1997) simultaneously model demand for and supply of IMF financing. Using a bivariate probit panel regression, they find that a low level of international reserve holdings or low per capita GDP is likely to be an important determinant of demand for IMF financing. Other variables include a high ratio of external debt service to export earnings, movements in the real exchange rate, weak growth of real per capita GDP, a low rate of domestic investment, and previous experience in implementing a policy program supported by IMF financing.

Two recent and most-related studies have attempted to find determinants of demand for the IMF's concessional financing from low-income countries. Bird and Rowlands (2009) examine whether the determinants of IMF financing vary across and within Fund-supported program countries classified as "classical, "capital account crisis" and "low income." They construct an econometric model and test it against these sub-samples using a panel probit regression. They find that the determinants are different between low-income and middle-income countries. In addition, they also find that recent engagement with the IMF is a reasonable predictor to contemporary IMF programs for both country groups. Bal Gündüz (2009) explores determinants of IMF financing for low-income countries. Her results indicate that several domestic and global variables are significant determinants of IMF financing. These domestic variables include reserves, the current account balance, real GDP growth, macroeconomic stability, and terms-of-trade shocks, while the global variables include changes in oil and non-oil commodity prices and world trade.

In summary, two interesting aspects of the demand side of IMF financing have not been explored in the literature. First, while the many above-mentioned variables likely hold for developing countries, on average, they do not necessarily hold for a specific developing country, which is the focus in any IMF financing arrangement. Second, the variables do not necessarily hold the highest predictive power for a specific country in forecasting its future concessional financing demand.

III. Stylized Facts

This section describes IMF financing arrangements and stylized facts of several variables prior to an IMF financial arrangement. Specifically, in addition to reporting a summary of IMF financing arrangements, we will present simple, but statistically significant, correlations between key economic variables prior to approval of an IMF financing arrangement and the subsequent number of arrangements.

A. Sample and Data

Our estimation sample includes 64 countries, 53 of which are PRGT-eligible and 11 which were previously PRGT-eligible, covering the period 1986-2018 (Appendix 1).[6][7] The sample selection is solely based on data availability. Our sample distribution is geographically skewed towards African countries, where most of the IMF financing arrangements are centered.

Regarding domestic and global factors, we examine nine different country-specific economic factors and eight global economic indicators commonly found in the literature. The sources

[6] A member is eligible for PRGT financing if (i) its annual per capita gross national income (GNI), based on the latest available qualifying data, is (a) below the International Development Association (IDA) operational cut-off; or (b) less than twice the IDA operational cut-off if the member qualifies as a small country; or (c) less than five times the IDA operational cut-off if the member qualifies as a "microstate"; and (ii) the sovereign does not have capacity to access international financial markets on a durable and substantial basis.

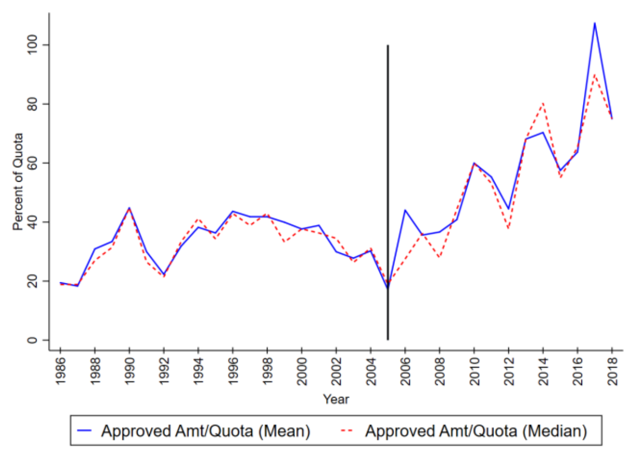
[7] The list of current and previously PRGT-eligible countries consists of 90 developing countries, twenty of which have already graduated (i.e., these countries are no longer eligible for IMF concessional financing). The sample includes all 36 countries that have benefited from HIPC debt relief.

of our annual data[8] include the World Economic Outlook (WEO), International Financial Statistics (IFS), Financial Flow Analysis (FFA), Haver, International Country Risk Guide (ICRG), and Emergency Events Database (EM-DAT) (Appendix 2).

B. Description of IMF Concessional Financing Arrangements

The IMF's concessional financing for eligible low-income countries began in the mid-1970s and has expanded significantly over time. The initial assistance was financed entirely through profits from the sale of IMF gold, first through Trust Fund (TF) loans and later through loans from the Structural Adjustment Facility (SAF). Since 1987, concessional loans have been financed in large part by bilateral contributions and have been extended through the Enhanced Structural Adjustment Facility (ESAF) Trust and its successors. The ESAF was renamed the Poverty Reduction and Growth Facility (PRGF) Trust in 1999, the Poverty Reduction and Growth Facility and Exogenous Shocks Facility (PRGF-ESF) Trust in 2006, and, since January 2010, the Poverty Reduction and Growth Trust (PRGT). A sweeping reform of concessional assistance in 2009 established two new facilities—the Standby Credit Facility (SCF) for short-term balance of payments needs and the Rapid Credit Facility (RCF) to provide low-access financing for urgent balance of payments needs—while continuing to address protracted balance of payments needs through the Extended Credit Facility (ECF). The Trust has seen more volatile and increased demand since 2005 (Figure 1).

Figure 1: Approved Amounts of PRGT-Financing per Quota



Sources: IMF database.

Table 1 shows different concessional financing arrangements in our sample. There are 391 arrangements in our sample. The table suggests that PRGT arrangements, on average, are extended beyond the original duration. A typical PRGT arrangement is usually more than three years, with an approved amount of about SDR 65 million (equivalent to 55 percent of quota).

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[8] The paper's use of third-party indicators for institutional variables is consistent with IMF guidance on the use of such indicators.

Table 1. Number of PRGT Financing Arrangements for Our Sample[1]

PRGT Arrangements Only	ECF	ESAF	ESF	PRGF	SAF	SCF	Total/ Median
Number of programs	62	86	11	71	23	5	260
Original duration (months)	36	36	12	36	36	18	36
Actual duration (months)	36	41	12	40	36	18	38
Approved Amount (percent of quota)	66	67	67	45	26	144	55
Approved amount (SDR million)	80	72	114	51	26	144	65

Sources: IMF database.

[1] SAF: Structural Adjustment Facility; ESAF: Enhanced Structural Adjustment Facility; ESF: Exogeneous Shock Facility; PRGF: Poverty Reduction and Growth Facility; ECF: Extended Concessional Facility; EFF: Extended Fund Facility.

C. Simple Correlations

Estimated ordinary least squares (OLS) coefficients show a significant correlation between the number of approved IMF financing arrangements and key economic variables prior to the approval of the arrangement in our sample (Table 2). These coefficients suggest that unfavorable developments in the external sector lead to a higher number of approved financing arrangements. In particular, large current account deficits, large external debt ratios, lower reserves, high volatility in U.S. financial markets, lower world economic growth, or low commodity prices tend to be correlated with a higher number of approved IMF financing arrangements in the future. Moreover, prolonged fiscal deficits, protracted low growth, and high inflation appear to be strongly correlated with a higher number of financing arrangements in the future. In summary, the simple correlations suggest that the dynamics of these variables contain useful information that may shed light on the factors of demand for IMF concessional financing arrangements.

Table 2. Simple Correlations[1]

Dependent Variables: Number of Financing Arrangements	Coefficients	Standard Errors
Lagged 4-year current account balance/GDP growth	-0.39***	0.12
4-year lagged external debt/GDP	0.07***	0.03
3-year lagged reserves	-0.00***	0.00
Cumulative sum of growth of volatility index (VIX)	1.68***	0.47
Lagged world GDP growth	-0.63*	0.31
3-year lagged commodity price index	-0.03**	0.01
Cumulative fiscal balance changes over the last 3 years	-0.88**	0.45
5-year cumulative sum of growth of real GDP per capita	-0.25***	0.11
4-year lagged consumer price index	-0.005***	0.02

Source: IMF staff calculation.

[1] Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Number of lags is selected based on the first statistically significant correlation.

IV. MODEL DESCRIPTION

This section presents the factor-augmented probit model toward identifying country-specific factors for the demand of IMF concessional financing resources.

A. Factor-Augmented Probit Model

Our factor-augmented probit model is a two-stage estimation procedure. In the first stage, a single-factor dynamic factor model is estimated for a set of variables. The estimated factor is essentially extracted signals from these variables to be used in the prediction step. In the second stage, a standard probit model is employed in which the estimated factor is utilized as the primary explanatory variable in lieu of the set of variables it is representing. The section below describes the method in detail.

A factor model is a popular dimension-reduction technique in statistics. The model decomposes a vector into a sum of two unobservable orthogonal components: a common component summarizing the factor common to all series (i.e., co-movement) and an idiosyncratic component specific to each series (i.e., measurement errors or series-specific features). Specifically, let $\boldsymbol{x}_{it} = \left[x_{i1t,\dots,}x_{ikt}\right]', t = 1 \dots T, i = 1 \dots N,$ be a vector of k stationary zero-mean time series for country *i*. The factor model is written as follows:

$$\boldsymbol{x}_{it} = \boldsymbol{\Lambda} \boldsymbol{f}_{it} + \boldsymbol{e}_{it} \tag{1}$$

where $\boldsymbol{\Lambda}$ is a $k \times r$ factor loading matrix, r is a small number of factors, which can be chosen by using an algorithm (for example, Bai and Ng, 2002), and $\boldsymbol{f}_{it} = \left[f_{i1t,\dots,}f_{irt}\right]$ are factors common to all x_t. The idiosyncratic disturbances $\boldsymbol{e}_{it}$ are assumed to be mutually uncorrelated at all leads and lags, i.e. $Ee_{ijt}e_{ims} = 0, \forall s$ if $j \neq m$. In the model above, $\boldsymbol{\Lambda f}_{it}$ is the common component, $\boldsymbol{e}_{it} = [e_{i1t}, \dots, e_{ikt}]$ is the idiosyncratic component.

The factors can be modeled as static or dynamic, leading to different variants of a dynamic factor model. A static factor model is written like equation (1) above (i.e., factors only have contemporaneous effects on $\boldsymbol{x}_{it}$). On the other hand, a dynamic factor model has the following form:

$$\begin{gathered}\boldsymbol{x}_{it} = \boldsymbol{\Lambda} \boldsymbol{f}_{it} + \boldsymbol{e}_{it} \\ \boldsymbol{f}_{it} = \lambda(\boldsymbol{L})\boldsymbol{f}_{it-1} + \boldsymbol{\eta}_{it}\end{gathered}$$

where L is the lag operator, $\boldsymbol{x}_{it}$ and $\boldsymbol{e}_{it}$ are $k \times 1$, $\boldsymbol{\eta}_{it}$ is $r \times 1$, $\boldsymbol{\Lambda}$ is a $k \times r$ factor loading matrix, and $\boldsymbol{\lambda}(\boldsymbol{L})$ is a $r \times r$ lag polynomial matrix. The idiosyncratic disturbances $\boldsymbol{e}_{it}$ are assumed to be uncorrelated with the factor innovations $\boldsymbol{\eta}_{it}$ at all leads and lags, i.e., $E\boldsymbol{e}_{it}\boldsymbol{\eta}'_{it-l} = 0, \forall i$. The number of dynamic factors can be determined by using the algorithm in Bai and Ng (2007).

For the final probit regression, let $y_{it}, i = 1 \dots N$, be a binary variable that takes the value of one when a country initiates a PRGT financing arrangement, and zero otherwise at time *t*. The one-step ahead forecast for the binary dependent variable is assumed to be:

$$E(y_{it+1}|y_{it}, \boldsymbol{f}_{it}, X_{it}, y_{it-1}, \boldsymbol{f}_{it-1}, X_{it-1}, \dots) = \alpha_i + \boldsymbol{\Gamma(L)}\boldsymbol{f}_{it} + \Phi(L)y_{it} + \psi(L)\boldsymbol{X}_{it}$$

where $\boldsymbol{\Gamma(L)}$, $\Phi(L)$, and $\psi(L)$ are lag polynomials, and $\boldsymbol{X}_{it}$ denotes country-specific institutional or other variables.

For our model specification, we choose to estimate a single dynamic common factor for a candidate set of factors. We do this for two main reasons: (*i*) to be consistent across all countries with varying variable set sizes—one factor as representation per country—and (*ii*) to accommodate the limited period sample size. Furthermore, we assume independent AR(2) processes for the dynamic factor, $\boldsymbol{f}_{it,}$ and the idiosyncratic shocks, $\boldsymbol{e}_{it}$: this is a common setup in the macro literature where dynamic factors are involved (Kim and Nelson (1994) and Otrok and Whiteman (1998)).

B. Data and Estimation Methodologies

To answer the paper's questions, we employ a three-step approach. To find the most informative variable set, we estimate the dynamic factor model country-by-country with all possible combinations of nine domestic and five global variables[9] using the maximum likelihood approach. After selecting the most informative set (see below for the selection criteria), we then use the selected estimated factor as the single lagged explanatory variable in the second-stage probit estimation for the country (Appendix 3). To obtain an aggregate forecast, we employ a statistical approach to first qualitatively describe the country-specific forecasts, then use the results in a beta regression (see section V.B for details).

The baseline calibration also accounts[10] for the years that a PRGT-eligible country was part of either one of the Heavily Indebted Poor Countries (HIPC) or Multilateral Debt Relief Initiatives (MDRI)[11] to control for the issue that IMF financing events may be highly correlated with IMF debt relief initiatives. When examining the role of institutional variables on the demand for IMF's concessional financing, we include, in addition to the estimated factor, no more than one institutional variable in the second-stage estimation. While it is possible to include the institutional variable in the first stage estimation, we excluded the

[9] We defined GDP per capita, inflation, current account balance, fiscal balance, government public debt, reserves, terms-of-trade, capital flows, and real effective exchange rate as domestic factors; and commodity price index, non-fuel and fuel price indices, oil price, and world GDP as global ones. While some of the domestic factors (capital flows and terms of trade) could be considered global, we defined them as domestic as they are not fully exogenous or out of the policy maker's control.

[10] We control for these events by setting the program dummy as one.

[11] Debt relief was previously also provided under the Multilateral Debt Relief Initiative (MDRI), which was intended to complement the HIPC Initiative by providing additional resources to help eligible countries achieve the United Nations Millennium Development Goals.

institutional variables from the dynamic factor model due to the disadvantages mentioned below and its lack of improvement in our prediction.

In selecting a particular set of variables for a country, we employ a statistical approach that balances four different criteria (Appendix 3): estimation precision (estimates with smaller confidence intervals), predictive power (being able to match historical events), information (lowest possible information criteria), and statistical significance (estimates with a degree of significance being at most 10 percent or lower). Upon obtaining all individual country-estimated results, we employ a statistical approach similar to those in Bal Gündüz (2009) and Demirgüc-Kunt and Detragiache (1999) to forecast aggregate demand for both historical and future program events.

Our estimation results are quite consistent across several robustness checks. Regarding the factor estimation step, we employ three different Bayesian estimation approaches presented in Jackson *et al.* (2016): principal component (the factor is the principal component), Kim and Nelson (1999) (factors are estimated using Kalman filter and Carter-Kohn sampling approach), and Otrok and Whiteman (1998) (obtaining the needed posterior distribution of factors conditional on parameters for Gibbs sampling). With respect to the second-stage probit estimation, as mentioned in Appendix 3, we also examined the cases in which the global variable is another independent lagged variable, in addition to the selected estimated lagged factor obtained from the first stage[12]. Regarding definitions of demand, the demand in our baseline results is defined by a dummy variable that has the value of one at the beginning of an IMF concessional financing arrangement and zero otherwise. For robustness checks, we examined an alternative definition of demand that the demand dummy variable will have the value of one for the entire duration of the IMF financial arrangement and zero otherwise. Within the context of the alternative definition of demand, we pursued a further robustness check of including lagged participation in an IMF financing arrangement as an explanatory dummy variable. The results presented in this paper either do not change with different estimation approaches or do not drastically change with regards to the alternative demand definition and model specifications.

There are advantages and disadvantages of this paper's estimation approach. One of the advantages is that it enables us to identify country-specific determinants of demand for IMF's PRGT financing. Another advantage is that the dynamic factor model allows us to extract signals from multiple variables for the second-stage probit estimation. On the other hand, the major disadvantage of this approach is that it only allows us to test the significance of the common estimated factor, a measure of co-movement across several variables, in influencing PRGT financing demand. In other words, this approach is unable to tell how a specific variable contributes to a country's financing demand. Another disadvantage is that the second-stage probit estimation relies on an estimated factor, which is subject to measurement errors. However, as mentioned earlier, we overcome this disadvantage by verifying the maximum likelihood estimation (MLE)-based results against those obtained by three different Bayesian approaches.

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[12] In this robustness check, we did not include global variables in the first-stage estimation.

V. RESULTS

A. Main Factors for the Demand for IMF Concessional Financing

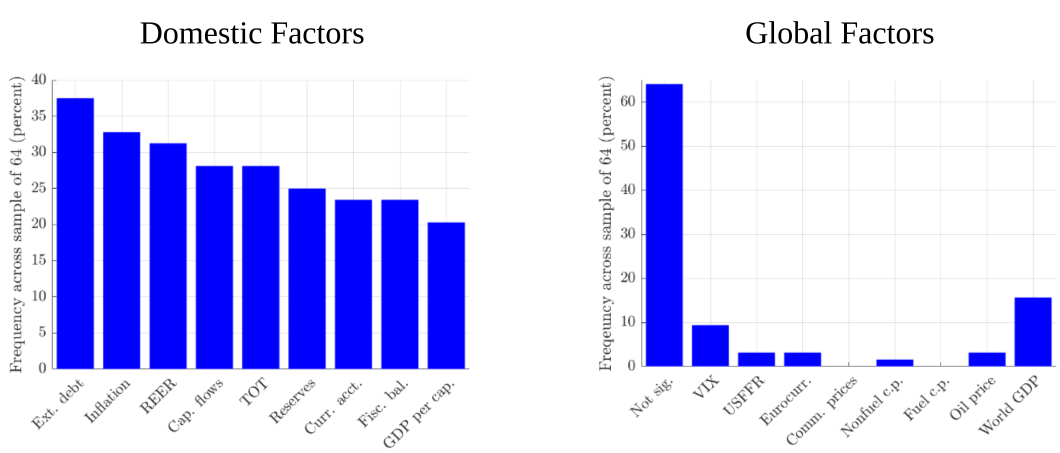
Country-specific factors

Domestic factors

Our estimation results indicate that domestic factors are the most important in influencing the demand for PRGT financing at the country level. Panel 1 of Figure 2 shows the frequencies at which each domestic factor appears in a statistically significant estimated factor in the second-stage probit estimation. There are three noticeable results:

- First, the factors that are statistically significant in more than 30 percent of the country-specific PRGT demand forecasts are factors that include external debt, inflation, and the real effective exchange rate (REER). It is worth noting two facts related to this result: (*i*) 16 (out of 64) countries in the sample do not have a REER series. Hence, the relative importance of REER could be understated; and (*ii*) external debt and inflation remain highly important factors under different definitions of demand.
- Second, capital flows, terms-of-trade, and international reserves are the next three most significant domestic factors, appearing as a significant factor for approximately a quarter of our sample.
- Third, the current account balance, fiscal balance, and GDP per capita growth are the least significant determinants of PRGT demand. While this finding is surprisingly different from the strong relationship between these factors and the number of approved programs seen in the stylized facts, this could mean that part of the explanatory power of these variables is being captured by other variables in the estimation.

Figure 2: Significant Domestic and Global Factors[1]



Source: IMF staff calculations.

[1] The statistical significance threshold for consideration corresponded to dynamic factors whose coefficient had a *p*-value of at most 0.1.

Global factors

We find that global factors are mostly statistically insignificant across our baseline and robustness check estimation. While this finding appears counter-intuitive, the informative power of these global variables may already be captured in some of the domestic factors. Panel 2 of Figure 2 shows the frequencies at which a global variable is found to be statistically significant.[13] Three noticeable results are visible in the chart:

- First, global factors do not seem to significantly improve the predictive capability of our model. They are not statistically significant for over 60 percent of our country sample.

- Second, world GDP growth and the U.S. financial market volatility index (VIX) have the most substantial weight in forecasting country-specific demand. This result is again consistent with those mentioned earlier in the stylized facts. Moreover, this suggests two possible external channels linked to requests for IMF financial arrangements from PRGT-eligible countries. A direct channel operates via export partners' lower growth that causes lower demand for commodities exported from PRGT countries. In addition to the export channel, weak world growth may potentially have an impact on the level of remittances received by low-income countries as well as financial support (through grants or concessional loans extended by partner countries) which could then have an impact on country-specific demand. An indirect channel functions via heightened uncertainties in U.S. financial markets that would cause financing difficulties in other financial markets, to which these PRGT countries may have access.

- Third, commodity prices, expressed either in terms of fuel and/or nonfuel prices, are also insignificant in forecasting demand for PRGT financing. Again, this could be due to the fact that the informative power of these global variables may already be captured in some of the domestic factors (e.g., terms-of-trade or external debt).

Institutional variables

Institutional variables are found to be significant predictors of demand for PRGT financing on a country-by-country basis. Table 3 shows the results for the countries that had an institutional variable being a significant predictor. Note that a negative coefficient on these institutional variables does not mean a lower likelihood of concessional borrowing since they are constructed such that higher values of these variables are associated with lower risks.

Two possible reasons could be underlying the lack of statistical significance for the institutional variables we used:

- ***Data issues***. Institutional data are lacking for most of our sample and available for a short period. Therefore, the significance of these variables (or the lack thereof) should be interpreted with caution.

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[13] Global factors were considered as explanatory variables in both the first-stage factor estimation and in the second-stage probit estimation as separate from the dynamic factor.

- ***Informational issues***. The financial and economic risk ratings are redundant in terms of information because the main set of domestic factors is able to explain most of the variation in the dependent variable.

Table 3: Significance of Institutional Variables[1]

Countries	Institutional Variables	Sign of the Coefficient	Significance Level
Benin	Natural disaster economic impact score	Negative	*
Ghana	Risk of democratic accountability	Positive	*
Guinea	Risk for foreign debt service	Positive	*
Côte d'Ivoire	Risk of law and order	Positive	*
Kenya	Risk of annual inflation rate	Positive	**
Madagascar	Risk of ethnic tensions	Negative	**
Mali	Risk of net international liquidity	Positive	*
Niger	Risk of exchange rate stability	Positive	*
Senegal	Risk of investment profile	Positive	**
Sierra Leone	Risk of exchange rate stability	Negative	*

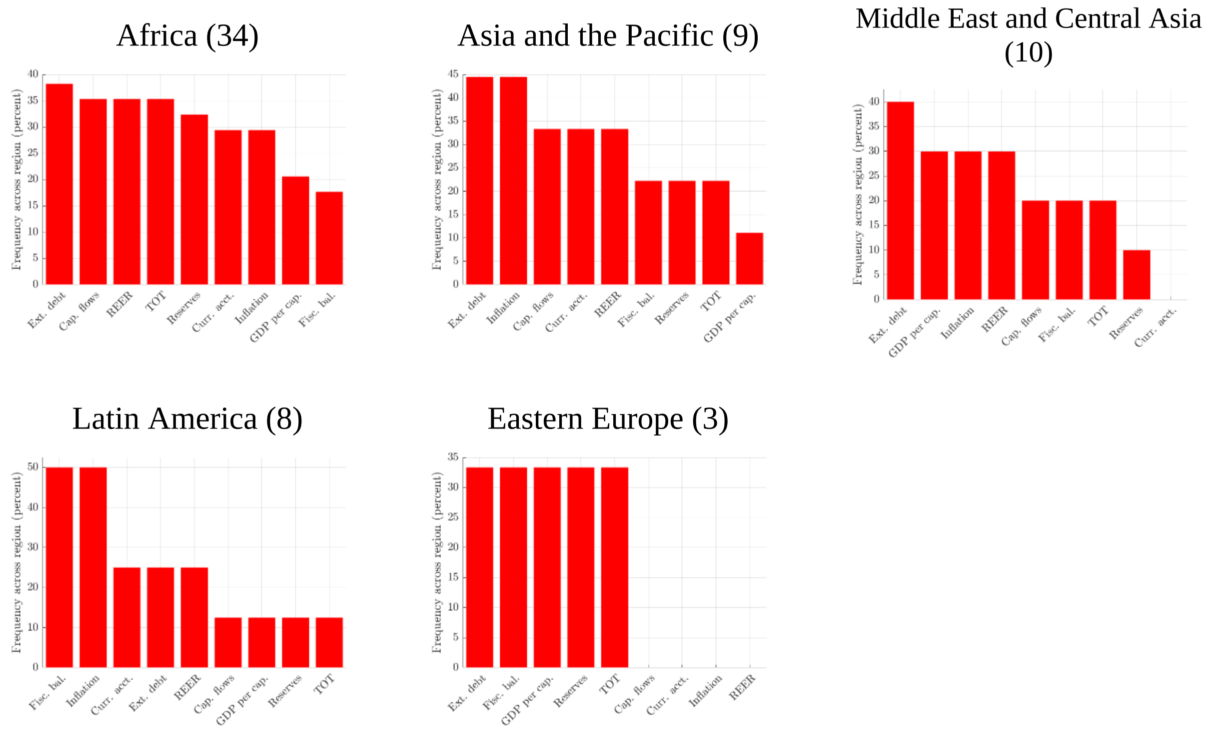
Sources: IMF staff calculations.

[1]The significance level corresponds to *** $p \leq 0.01$, ** $p \leq 0.05$, and * $p \leq 0.1$. It is important to note that the risk indices denote a higher risk for lower index values, and lower risk for higher index values.

Regional factors of demand for concessional financing

The three major factors found earlier continue playing major roles at regional levels. Figure 3 shows the same type of domestic factor analysis shown in Chart 1 of Figure 2. External debt is constantly ranked as the most important factor of demand for all but Latin America where the fiscal balance plays a more prominent role. Inflation is also among the three most important factors in all but two regions. Furthermore, REER continues to be among the five major factors in all but one region. Lastly, fiscal balances and GDP growth play a varying role among regions.

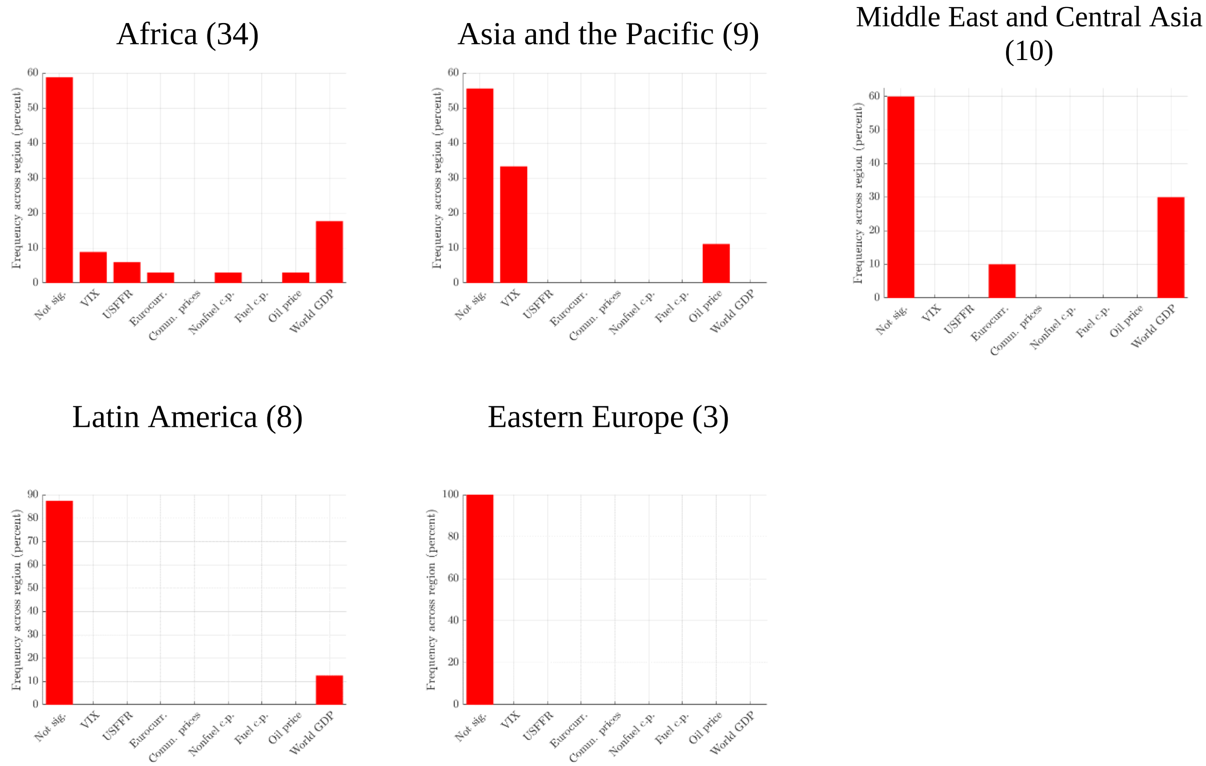
Figure 3: Regional Domestic Factors[1]



Source: IMF staff calculations.
[1] Sample size for each region is in parenthesis.

Global factors generally still do not seem to be an important factor influencing the demand for concessional financing at regional levels. Figure 4 shows the regional analogue to Figure 3, depicting the frequency at which global determinants proved significant within a regional group. These charts indicate that world GDP growth continues to be a nontrivial factor for the majority of the regions, with the exceptions of Asia and Pacific and Eastern Europe. It also shows that volatilities in U.S. financial markets (VIX) is a significant indicator of demand for Asian and Pacific countries. The reason underlying this result could be that the U.S. and other Western economies are major trade partners with countries in this region. In addition, several Asia and Pacific countries rely heavily on tourism, which may increase their exposure to external markets.

Figure 4: Regional Significant Global Factors[1]



Source: IMF staff calculation.

[1] Sample size for each region is in parenthesis.

In summary, we find that domestic variables, in particular, external debt, inflation, and the REER, hold the power to predict the demand for PRGT financing. Global factors, on the other hand, do not seem to improve the prediction power as the informative power of these global variables may already be captured in some of the domestic factors.

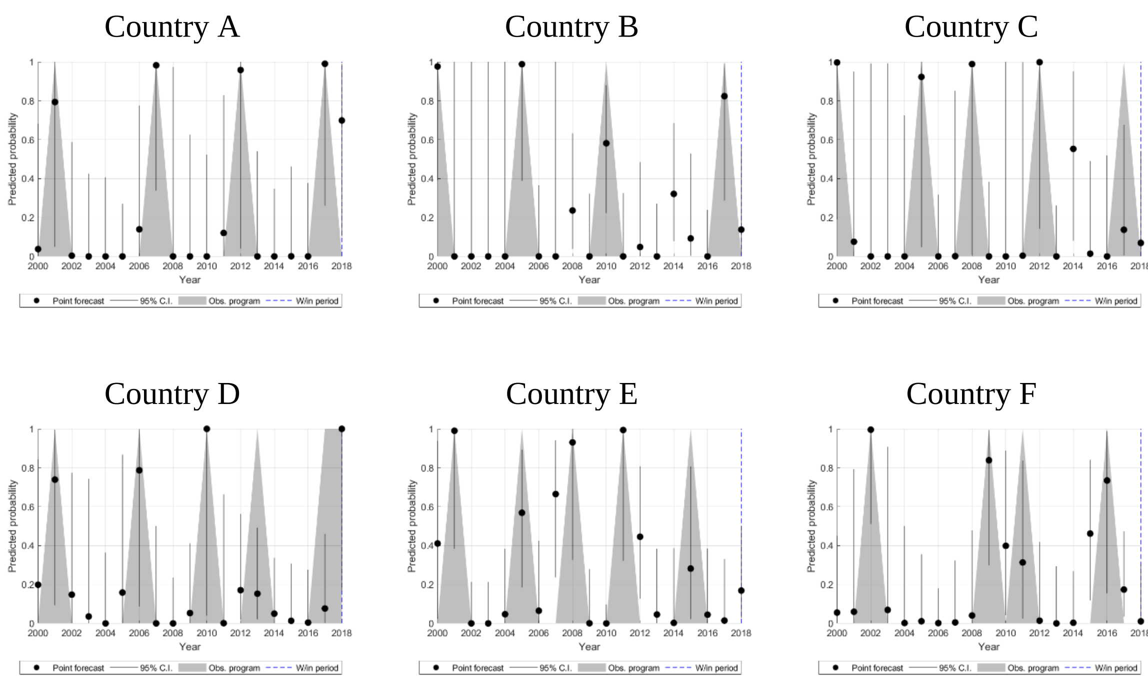
B. Model Forecasts

The forecasting capability of the model at the country and aggregate levels is presented in this section. As presented below, this paper's statistical approach provides significant forecasting capabilities at both levels. Such forecast capability can complement demand analyses of IMF concessional financing at both the country and aggregate levels.

Country-specific demand forecasts

Our statistical approach allows for country-specific PRGT demand forecasts tailored to each individual country, rather than the on-average/cross-sectional approach that has been done in the literature. Due to the economic sensitivity of the prediction, we only illustrate examples of country-specific forecasts for six countries in our sample in Figure 5 without labeling them. Any forecasts that appear after the blue-dashed line are out-of-period forecasts. The shaded areas indicate the time when a financing arrangement was approved. As seen in the figure, the modeling approach provides quite accurate forecasts of historical events. Generally, higher point estimates appear where an actual IMF PRGT financing arrangement is approved, and lower probabilities when a country has not requested or been approved for a financing arrangement.

Figure 5: Country-Specific Forecasts



Source: IMF staff calculations.

A qualitative and aggregate forecasting framework

Qualitative forecasts and aggregate forecasts are helpful in their own right. Qualitative forecasts provide an assessment about the risk level of a forecast. Aggregate forecasts, on the other hand, provide the probability of aggregate demand for concessional financing in the next period. These forecasts are useful in evaluating country-specific risks of applying for IMF financing as well as providing aggregate forecasts for PRGT financing demand.

Bal Gündüz (2009) and Demirgüc-Kunt and Detragiache (1999) rely on hypothesis testing to construct risk or vulnerability regions to then qualitatively describe the economic state of a country. They use ad hoc weights on type I and type II errors to make classifications that fit within different forecasted probability regions.

In lieu of ad hoc type I and type II objective weights, we believe that a statistically appropriate way of identifying risk regions may rely on the objective of providing the most significant aggregate demand forecasts. Our approach allows us to construct a qualitative forecasting framework that identifies both the number of risk regions for classification, as well as the probability thresholds for each region, similar to Bal Gündüz (2009) and

Demirgüc-Kunt and Detragiache (1999). Consequently, the proposed approach presented below is based on sound statistical inference.

For a given number of risk regions, J, we calibrate the probability thresholds that minimize the root mean squared error[14] and maximizes the Pseudo R^2 of the following beta regression:[15]

$$g(\mu_t) = \beta_0 + \sum_{j=1}^{J} \beta_j \, x_{jt}$$

where $g(\cdot)$ is a link function (we use a logit-link function), μ_t is the mean of a beta density with unknown precision parameter ϕ for the dependent variable y_t[16]–which we define as the proportion of countries that apply for and are approved for an IMF concessional financing arrangement in a given year t; β_0 is a constant term, and x_{jt} is the fraction of countries eligible for concessional financing forecasted to be within risk group j for a given year and for given probability thresholds. The parameters that are estimated are β_i for $i = 0,1, \ldots, J$ and ϕ.

We find that four risk regions with probability thresholds of 0.2252, 0.5383, and 0.7710 minimize RMSE and maximize the Pseudo R^2.[17] Figure 6 depicts the calibrated risk regions with type I and type II errors shown for comparison.[18]

These thresholds are then applied to country-specific forecasts. The results shown in Figure 5 are repeated in Figure 7 below where each country-specific forecast is assigned a qualitative assessment. It is apparent from the figure that the qualitative forecasts provide an intuitive and informative valuation of the riskiness of each forecast for each country.

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[14] $RMSE = \sqrt{\frac{1}{T}\sum_t (y_t - \hat{y}_t)^2}$.

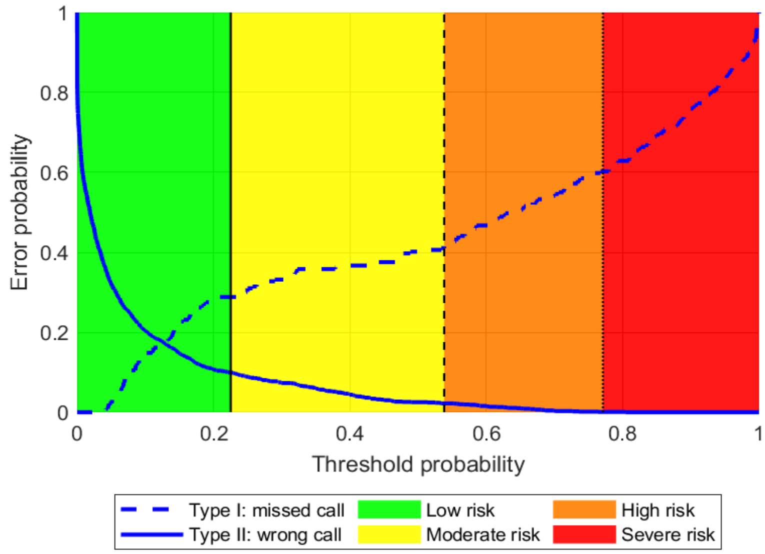
[15] See Ferrari and Cribari-Neto (2004). MATLAB code was written by Willem-Jan de Goeij, 2009. Since we set up a regression that is forecasting proportions, it is more appropriate to use a beta regression than OLS as the latter would allow for values outside of zero and one.

[16] It is assumed that $y_t \sim iid\ Beta(\mu_t, \phi)$ for all t.

[17] We considered having anywhere from two to five risk regions.

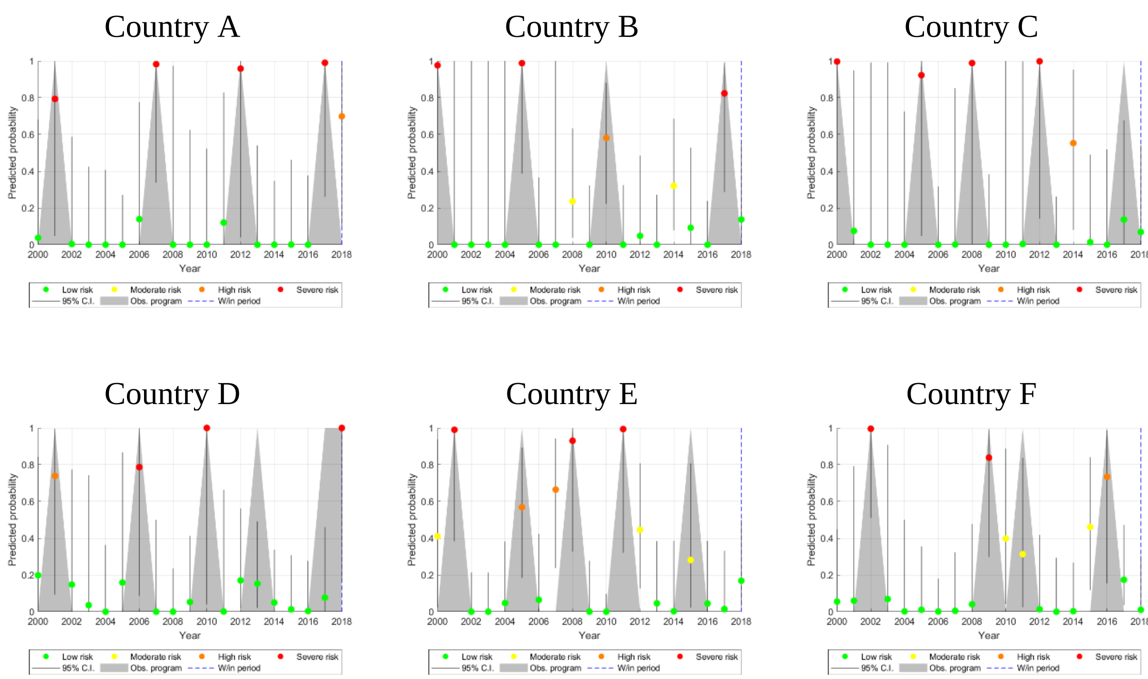
[18] The hypothesis being tested is that of a PRGT-eligible country initiating a PRGT arrangement, $H_0\colon y_{i,t} = 1$, as opposed to not starting a concessional financing arrangement, $H_a\colon y_{i,t} = 0$.

Figure 6: Qualitative Forecasting Framework



Source: IMF staff calculations.

Figure 7: Country-Specific Model Forecasts, with Risk Classifications



Source: IMF staff calculations.

These country-specific qualitative forecasts can be used to obtain aggregate demand forecasts. We calculate the share of each risk group based on the qualitative forecasts and the share of countries approved for IMF concessional financing (i.e., a measure of aggregate demand) in our sample for each year. We then run a beta regression of the latter on the former. The regression results are presented in Table 4, and Figure 8 presents the aggregate forecasts visually. As shown in the table, the statistical significance of severe risk and low risk groups is intuitive: the higher the risk classification is, the higher the forecasted aggregate demand for concessional financing will be, while lower risk classifications will forecast lower aggregate demand. While the two middle risk groups have signs opposite to what is anticipated, their estimates are insignificant, and the results may change as more data are added and the thresholds are adjusted—the current data range (number of observations) for this aggregate forecasting exercise is 31 years.

Table 4: Beta Regression Results of Aggregate Demand[1]

Dependent Variable: Annual Share of Countries in IMF Concessional Financing Arrangements	Coefficients (SE)
Constant, $\boldsymbol{\beta_0}$	-1.83***
	(0.28)
Severe risk group ($\hat{\boldsymbol{p}} \geq \mathbf{0.7710}$), $\boldsymbol{\beta_1}$	11.39***
	(2.18)
High risk ($\mathbf{0.7710} > \hat{\boldsymbol{p}} \geq \mathbf{0.5383}$), $\boldsymbol{\beta_2}$	-5.07
	(3.34)
Moderate risk ($\mathbf{0.5383} > \hat{\boldsymbol{p}} \geq \mathbf{0.2252}$), $\boldsymbol{\beta_3}$	1.72
	(1.73)
Low risk ($\mathbf{0.2252} > \hat{\boldsymbol{p}}$), $\boldsymbol{\beta_4}$	-1.13***
	(0.45)
Precision parameter, $\boldsymbol{\phi}$	107.06***
	(27.22)
Pseudo $\boldsymbol{R^2}$	0.5580
RMSE	0.0297
Number of observations (years)	31

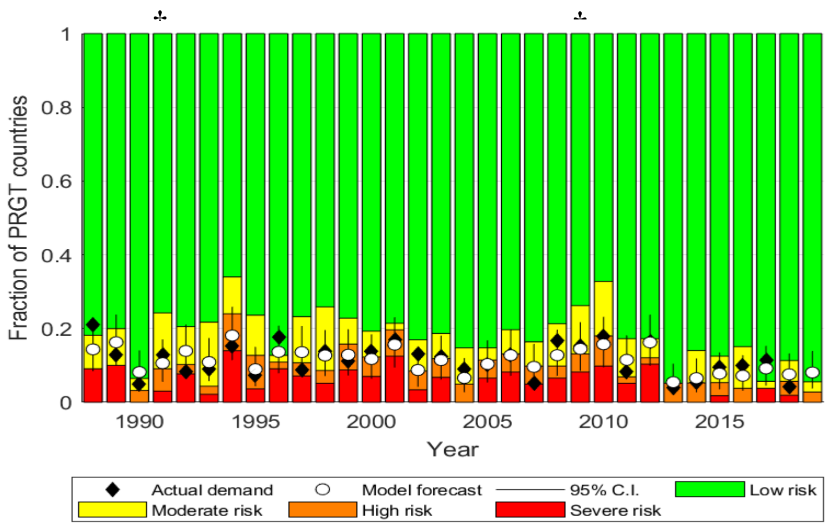
Source: IMF staff calculations.

[1]Standard errors in parenthesis. $\hat{p}$ refers to the predicted probability from the country-specific demand models. *** $p \leq 0.01$, ** $p \leq 0.05$, and * $p \leq 0.1$.

Figure 8 shows the within (all years up to 2018) and out-of-period (2019) forecasts for aggregate demand for concessional financing, actual aggregate demand for concessional financing in each year, and the relative size of the risk groups within each year's sample. Only those countries eligible for concessional financing with at least one significant predictor[19] in its country-specific demand model were included in each year's sample. Each risk group is of a non-trivial size, and that model forecasts perform fairly well, capturing actual demand within the 95 percent confidence interval for each year.

[19] A p-value of at most 0.1.

Figure 8: Aggregate Demand Model Forecasts[1]



Source: IMF staff calculation.
[1] † denotes a global recession year, as defined by the IMF (IMF (1991), IMF (2009)).

VI. Conclusions

This paper attempts to find major country-specific and global factors of demand for IMF concessional financing. Using a two-step econometric model and a balanced statistical approach to select a set of factors for each country, we find that key country-specific factors of demand vary among countries eligible for IMF concessional financing. The most common country-specific economic factors among countries eligible for concessional financing include external debt, inflation, and the real effective exchange rate (REER). These three major factors are also significant in driving demand at regional levels. However, global factors are mostly insignificant across countries and regional cohorts. This paper's approach also has significant capability to predict historical events at the country-level. This study also seeks to obtain aggregate forecasts based on qualitative forecasting, which provide inputs toward forecasting aggregate demand for IMF concessional financing.

This paper's empirical results have implications for policy recommendations as well as helping manage the IMF's limited resources for concessional financing. The results indicate that factors are country-specific. Moreover, unfavorable developments in the external, real, and fiscal sectors coupled with country-specific institutional conditions are linked to demand for IMF concessional financing. Consequently, maintaining sustainable external debt, lower inflation, strengthening fiscal positions, and improving GDP growth and governance could potentially reduce demand for concessional lending.

For future research, this paper's approach could be applied to finding country-specific determinants of demand for the IMF's non-concessional financing and examining the impact of the COVID-19 pandemic on demand. Another interesting direction would be simplifying the estimation approach by applying a dynamic factor model with Markov-switching.

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Appendix 1. Geographical Country Sample

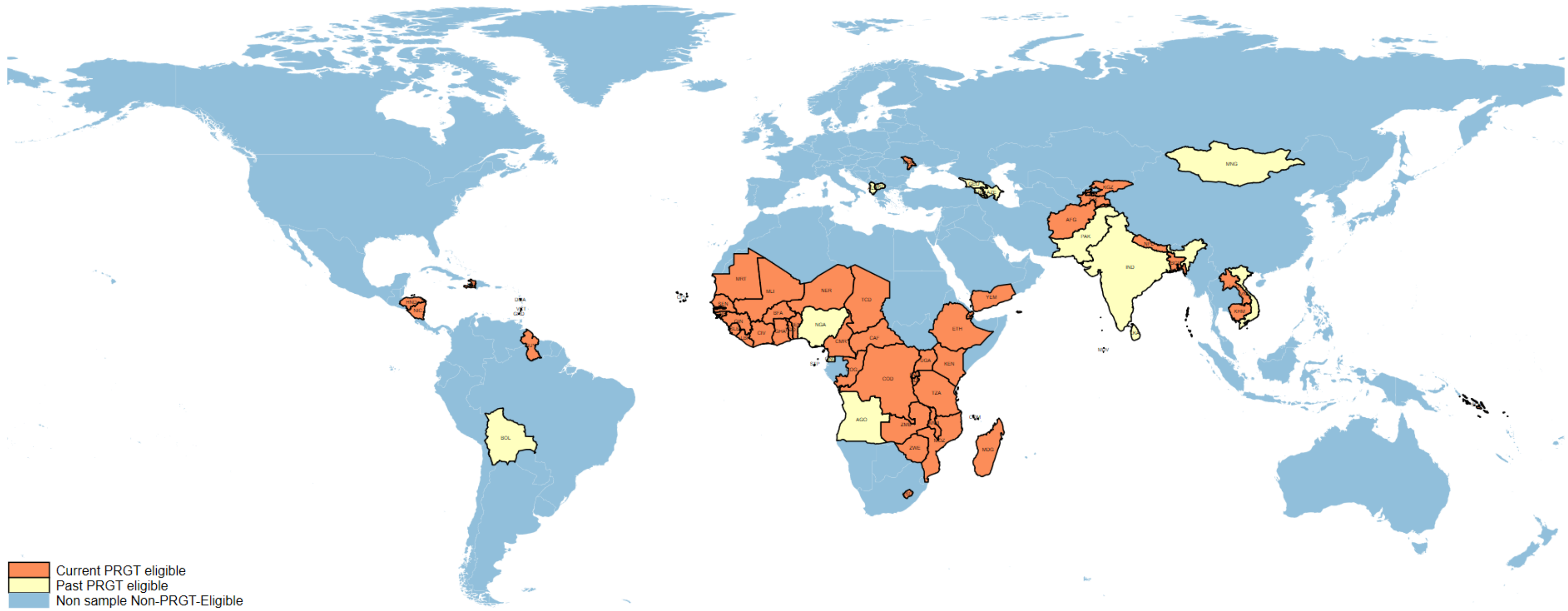


Table 5. Country Sample

Country	Country	Country	Country	Country	Country	Country	Country
Afghanistan*	Burundi*	Djibouti	Guinea-Bissau*	Liberia*	Mongolia	Rwanda*	Tanzania*
Albania	Cambodia	Dominica	Guyana*	Macedonia	Mozambique	St Vincent&Grenada*	Gambia*
Armenia	Cameroon*	Eq. Guinea	Haiti*	Madagascar*	Nepal	São Tomé&Principe*	Togo*
Azerbaijan	Cen. Afr. Rep.*	Ethiopia*	Honduras*	Malawi*	Nicaragua*	Senegal*	Uganda*
Bangladesh	Chad*	Georgia	Kenya	Maldives	Niger*	Sierra Leone*	Vietnam
Benin*	Comoros*	Ghana*	Kyrgyzstan	Mali*	Pakistan	Solomon Islands	Yemen
Bolivia*	Côte d'Ivoire*	Grenada	Lao PDR	Mauritania*	Cabo Verde	Sri Lanka	Zambia*
Burkina Faso*	Dem. Rep. Congo*	Guinea*	Lesotho	Moldova	Rep. Congo*	Tajikistan	Zimbabwe

Source: IMF's Finance Department. * Denotes HIPC countries.

Appendix 2. Data Description and Source

Variables	Data Description	Source
Gross domestic product	Percent change of gross domestic product per capita at constant prices in national currency	WEO
Inflation	Period average of percent change of consumer prices	WEO
Current account balance	Net total current account as percent of GDP	WEO
Fiscal balance	Budget balance as percent of GDP	WEO
External debt	Total external debt (U.S. dollars) as percent of GDP	WEO
Reserves	Total reserves (excluding gold) in US dollars	WEO
Terms of trade	Growth of terms of trade	WEO
Capital inflows	Total net inflows (in U.S. dollars) as percent of GDP	Financial Flow Analysis (Internal database)
VIX	CBOE new volatility index	Haver
U.S. federal fund rate	End-of-period U.S. Federal Funds rate	Haver
Commodity price index	Commodity price index	WEO
Euro rate	End-of-period 1-month Euro deposit	Haver
Real effective exchange rate	Real effective exchange rate	IFS
Risk of external conflict	The external conflict measure is an assessment both of the risk to the incumbent government from foreign action, ranging from non-violent external pressure (diplomatic pressures, withholding of aid, trade restrictions, territorial disputes, sanctions, etc.) to violent external pressure (cross-border conflicts to all-out war)	ICRG
Risk of ethnic tensions	This component is an assessment of the degree of tension within a country attributable to racial, nationality, or language divisions. Lower ratings are given to countries where racial and nationality tensions are high because opposing groups are intolerant and unwilling to compromise. Higher ratings are given to countries where tensions are minimal, even though such differences may still exist	ICRG
Risk of law and order	“Law and order” form a single component, but its two elements are assessed separately, with each element being scored from zero to three points. To assess the “law” element, the strength and impartiality of the legal system are considered, while the “order” element is an assessment of popular observance of the law	ICRG

Variables	Data Description	Source
Risk of annual inflation rate	The estimated annual inflation rate (the unweighted average of the consumer price index) is calculated as a percentage change. The risk points are then assigned according to a specified scale	ICRG
Risk of net international liquidity	The total estimated official reserves for a given year, converted into US dollars at the average exchange rate for that year, including official holdings of gold, converted into U.S. dollars at the free market price for the period, but excluding the use of IMF credits and the foreign liabilities of the monetary authorities, is divided by the average monthly merchandise import cost, converted into U.S. dollars at the average exchange rate for the period. This provides a comparative liquidity risk ratio that indicates how many months of imports can be financed with reserves. The risk points are then assigned according to a specified scale	ICRG
Risk of exchange rate stability	The appreciation or depreciation of a currency against the U.S. dollar over a calendar year or the most recent 12-month period is calculated as a percentage change. The risk points are then assigned according to the specified scale for appreciation and depreciation	ICRG
Risk of investment profile	This is an assessment of factors affecting the risk to investment that are not covered by other political, economic and financial risk components. The risk rating assigned is the sum of three subcomponents, each with a maximum score of four points and a minimum score of zero	ICRG
Risk of foreign debt service, percent of exports of goods and services	The estimated foreign debt service, for a given year, converted into U.S. dollars at the average exchange rate for that year, is expressed as a percentage of the sum of the estimated total exports of goods and services for that year, converted into U.S. dollars at the average exchange rate for that year. The risk points are then assigned according to a specified scale	ICRG
Risk of democratic accountability	This is a measure of how responsive government is to its people, on the basis that the less responsive it is, the more likely it is that the government will fall, peacefully in a democratic society, but possibly violently in a non-democratic one. The points in this component are awarded on the basis of the type of governance enjoyed by the country in question	ICRG

Appendix 3. Model Selection

Country-specific factors for the demand of IMF concessional financing were determined via a statistical approach balancing the measures of predictive power, model precision, informational quality, and statistical significance. The first three measures were used in identifying the set of variables in each country-specific demand model, and the latter measure was used as the final cut for a model to be included in the aggregate results presented in the paper.

The model's predictive power was measured by the commonly used Brier's quadratic probability score (see Brier (1950)). This score is the probability analogue to the root mean square error commonly reported in ordinary least squares regressions:

$$QPS_i = \frac{1}{T}\sum_{t=0}^{T-1}\left(y_{it+1} - E(y_{it+1}|y_{it}, \boldsymbol{f}_{it}, X_{it}, y_{it-1}, \boldsymbol{f}_{it-1}, X_{it-1}, \dots)\right)^2,$$

where i indexes the country, t indexes time, y_{it+1} is the observed demand (i.e., program indicator has value of one) for PRGT resources, and $E(y_{it+1}|y_{it}, \boldsymbol{f}_{it}, X_{it}, y_{it-1}, \boldsymbol{f}_{it-1}, X_{it-1}, \dots)$ is the model's probability prediction of demand given the information available at time t. A desirable quality is for QPS to be close to zero.

For model precision, we choose to compute a score derived from the 95 percent confidence bands of the within-period probability forecasts. We find this measure to be particularly important to exclude explosive model estimates that are common with small-sample predictions. We define the confidence score as:

$$CS_i = \frac{\delta}{T}\sum_{t=0}^{T-1} range\left(CI_{it+1}(E(y_{it+1}|y_{it}, \boldsymbol{f}_{it}, X_{it}, y_{it-1}, \boldsymbol{f}_{it-1}, X_{it-1}, \dots)|\alpha = 0.05)\right),$$

where δ is a scaling parameter,[20] $CI_{it+1}(E(y_{it+1}|y_{it}, \boldsymbol{f}_{it}, X_{it}, y_{it-1}, \boldsymbol{f}_{it-1}, X_{it-1}, \dots)|\alpha = 0.05)$ is the 95 percent confidence interval of a country's probability forecast for a particular period, and $range(\cdot)$ denotes the difference between the points corresponding to the top and bottom band of the confidence interval. Just as the QPS, a lower (closer to zero) CS is more desirable.

The last criterion used for variable selection is the Akaike Information Criterion (AIC). Given the few numbers of instances a country may apply for concessional financing from the IMF, and the few numbers of periods available in the data, it is important that the set of variables provides informative predictive measures. The AIC provides a sense of informational quality of a particular set of factors relative to another:

$$AIC_i = 2k - 2\log(\hat{L}),$$

where k is the number of estimated parameters, and $\hat{L}$ denotes the maximized likelihood of the probabilistic model for a given set of variables. To make the comparison across the varying

[20] We set $\delta = \frac{1}{4}$ to be comparable in magnitude with that of the QPS.

period lengths of the various sets of variables, we normalize this criterion by the number of periods, T.

Given that the improvement of one of these criteria does not imply an improvement of the other two criteria, we chose to weight these three measures-QPS, CS, AIC-equally when making our initial variable selection for each country. Our objective function for each country i could then be generally described as:

$$\omega_{QPS} QPS_i + \omega_{CS} CS_i + \omega_{AIC} AIC_i,$$

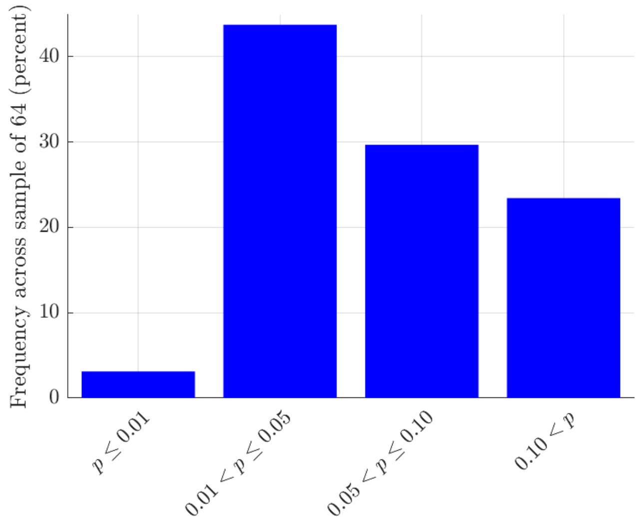
where $\omega_{QPS} + \omega_{CS} + \omega_{AIC} = 1$.[21] We chose the set of variables that minimized this objective function, double checking to ensure that the estimates were non-explosive (i.e. $Pseudo\ R^2 < 1$).

Country-specific factors were determined in three stages: domestic factors, global factors, and other/institutional factors. After the set of domestic factors was determined via the minimization approach just described, we then looked at including (no more than) one global factor to determine if the objective function could improve: the global factor was included either inside the dynamic factor model or as a separate explanatory variable in the probit model. The last stage considered including (no more than) one other/institutional variable outside of the dynamic factor model.

Statistical significance was the last criterion requisite toward including a model's predictions/results for the final analyses presented in this paper. Only those with a *p*-value of at most 0.1 were included. To provide an idea as to the effectiveness of our statistical approach, the following figure provides the frequency of significance of the coefficient on the estimated common factor in the probabilistic regression across the entire country sample (64). It is clear that the majority of common factors proved to be significant in forecasting demand for PRGT resources. Furthermore, the average QPS, CI, and AIC for the final selected models across all countries (regardless of significance) was 0.064, 0.099, and 0.626, respectively, with an average Pseudo R^2 equal to 0.443.

[21] We set $\omega_{QPS} = \omega_{CS} = \omega_{AIC} = \frac{1}{3}$.

Figure 9: Dynamic Factor Significance in the Probit Regression



Source: IMF staff calculations.