

The Accuracy of IMF Crises Nowcasts ^{*}

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Abstract

The International Monetary Fund (IMF) provides loans to countries in economic crises as lender of last resort. Loan approval is tied to policy reforms and quantitative targets that are contingent on the IMF’s crisis assessment. An extensive literature scrutinizes the efficacy of IMF loan programs, instead we examine the accuracy of the IMF’s assessments of crisis conditions (nowcasts) that predicate program design. Analyzing an unprecedented 602 IMF loan programs from 1992 to 2019, we contradict the popular notion that IMF forecasts are generally optimistic. By disentangling the structure of the nowcast bias, we find the IMF systematically overestimates low-growth recoveries for Low-Income Countries’ (LICs) GDPs while underestimating high-growth recoveries. Our unusually large sample allows us to document that Non-LICs nowcasts exhibit no statistically significant optimistic/pessimistic bias. We isolate the sources of inefficiencies in IMF nowcasts, including: (i) program objectives, (ii) program conditionality, (iii) geographic regions, (iv) global crises, and (v) geopolitics (elections, conflicts, disasters). In addition, we show that shorter nowcast horizons do not improve accuracy, and that GDP growth nowcasts improved substantially since 2013. Inflation nowcasts continue to struggle with efficiency as recently as 2018.

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*Most forecasts are wrong, but some are useful*¹

I Introduction

The core mission of the International Monetary Fund (IMF) is to ensure the stability of the global economy through surveillance of member economies and lending to crisis countries (IMF, 2020e). As global lender of last resort, IMF crisis loan programs stipulate policy conditions and quantitative economic targets which must be implemented before loan tranches are disbursed (Fischer, 1999). IMF program design and conditionality can be contentious, since the fundamentals of countries' crises often require substantial and often unpopular policy changes to ameliorate the economic conditions that IMF nowcasts establish at the time of crisis.² IMF nowcasts thus constitute a unique dataset to evaluate the accuracy of the assumptions that constitute the basis for IMF program types, conditions, and loan sizes.³ Another important dimension of nowcast accuracy are country program performance evaluations and loan tranche disbursements, which depend on benchmarks established on the basis of the original nowcasts. Thus nowcast bias and/or inefficiency influence not only program scope and design, but also the apparent magnitude and speed of recoveries (Park, 2006, Chapter 9).

According to Nordhaus (1987), nowcasts are unbiased and efficient when they incorporate all relevant information available at the time that nowcasts are established. There have been a number of evaluations of IMF forecasts, IMF conditionality, and IMF program efficacy, but previous evaluations focus largely on official final data from the IMF's World Economic Outlook (WEO) database, not actual crisis nowcast data.⁴ The dataset we use in this paper predates any WEO entries and representing unique, long confidential snapshots of the IMF's understanding of economies at the pinnacles of crises.

Eicher et al. (2019, EKPC from here forward) also formally examined the accuracy of IMF nowcasts using actual crisis data, not the WEO data. They did not explore the possible

¹Variant of George Box's (1976) statistical aphorism.

²See e.g., Feldstein (1998), Stiglitz (2002), who all attribute slow crisis recoveries to IMF conditionality.

³IMF crisis program designs rely on assessments of the current states of the economy. Such one-off forecasts are best described as "nowcasts" as they have to be based on interim data in lieu of the arrival of regular data vintages, see Baíbura et al. (2011). Some IMF programs include up to 4-year forecasts, but in this paper we examine only nowcasts produced during the crisis year, for the crisis year.

⁴See among others: Artis (1988), Artis (1997); Barrionuevo (1993); Beach & Schavey (1999); Loungani (2001); Batchelor (2001); Pons (2000); Aldenhoff (2007); Timmermann (2007). Similar to Batchelor, Beach et al. find IMF WEO forecasts for developing countries overestimate real GDP growth and underestimate inflation, while forecasts for industrialized nations are unbiased and efficient. Artis and Loungani compare IMF forecasts to consensus forecasts and find no substantial differences. Neither of these papers focus on countries in crises or forecasts in times of crises.

sources of bias and inefficiencies, as we do below. EKPC also examined only 110 out of 602 available programs and excluded a large share of observations due to concerns for outliers and database errors. We audit the IMF program database, and verify that about one-third of EKPC's excluded programs should have been included. Large outliers are simply a defining characteristic of countries requiring IMF crisis assistance. Our audit of the IMF's Monitoring of Fund Arrangements (MONA) database also allowed us to include an additional 492 programs and an additional 14 years of nowcast data.⁵ To evaluate nowcasts, EKPC used estimates of final data, not official final data which differ substantially (see Figure 1). Only 57% of the data lie within 1% of each other, hence EKPC's nowcast assessments and results are contaminated by final data errors. Most important, however, is our exploration of the sources of bias and inefficiency in IMF nowcasts, focusing on information IMF economists possessed at the time of the nowcasts.

We introduce several groups of covariates to examine whether their effects were properly accounted for by IMF nowcasts, or whether they were sources of IMF nowcasts' inefficiencies. These regressors relate to (i) international crises, (ii) geographic regions, (iii) conditionality (quantitative and structural performance criteria), (iv) program objectives, (v) loan amount and loan cancellation, (vi) elections, (vii) conflicts, and (viii) natural disasters. Inflation, nominal, and real GDP growth are shown to be associated with different types of conditionality and program aspects that were not properly integrated into IMF nowcasts. For inflation, conditionality effects of ceilings on government deficits and debt were underestimated in IMF nowcasts. For real GDP, ceilings on government credit were overestimated. Nominal GDP features the largest number of conditionality effects improperly integrated into nowcasts, namely ceilings on external debt/arrears, ceilings on government deficit/debt, and reforms of the current/capital accounts.

EKPC found inflation nowcasts to be unbiased and efficient. Using the additionally available programs and official (not estimated) final data that our audit produced, we find IMF inflation nowcasts are actually biased and inefficient. EKPC also found nominal GDP growth nowcasts unbiased and efficient, but our expanded dataset shows both nominal and real GDP growth nowcasts to be inefficient, systematically overestimating low-growth crisis recoveries and underestimating high-growth recoveries. [Luna \(2014\)](#) previously studied and even smaller sample of 94 program countries and found that optimism in IMF crisis forecasts was driven by countries with large loans, but our results in a substantially larger and longer sample do not confirm that loan size affects bias or inefficiency. [Luna \(2014\)](#) also suggested that optimism in IMF forecasts may reflect inadequate program execution on the part of

⁵ Appendix A1 documents our audit of the database, detailing 11 different types of errors and corrections.

the countries, but we find no evidence that cancelled programs affect nowcast efficiency.⁶ It is generally expected that forecasts improve as time horizons shorten and [IMF-IEO \(2014\)](#) established the same for WEO forecasts. In contrast, we find that this is not the case for IMF crisis countries nowcasts, which are equally likely to be inefficient and/or biased early or late in the program year for which the nowcast was established. However, exploiting our 28-year time series, we can document that recent GDP growth nowcast accuracy has improved dramatically, while inflation nowcasts continue to struggle with inefficiency until recently.

A voluminous literature describes a common theme that IMF forecasts are thought to be optimistic.⁷ For crisis countries, we show that a focus on average forecast errors, without formal tests, in small samples, provides misleading results. Our approach is novel in that our large sample allows formal tests that decompose the perceived optimism to lay bare the structure of the nowcast inefficiency. The particular manner in which optimistic and pessimistic forecasts average out for high and low-growth crisis recoveries is shown to contain important information. We show that IMF optimism is only a feature for low-growth recoveries in LICs while fast recovering program countries actually suffer from excessively pessimistic IMF nowcasts. Once LICs are purged from the sample, we produce the important result that the remaining share of nearly 250 nowcasts are actually unbiased and efficient.

Overly optimistic nowcasts for low-growth recoveries may lead to an underestimate of the required financial support and quantitative/reform adjustments. Also, overly optimistic nowcasts for slow-growth recoveries may translate into overly optimistic program targets that are too difficult to reach. LICs' nowcasts are shown to exhibit the greatest inefficiencies and by far the most optimistic nowcasts for low-growth recoveries. Most unsettling, [Beaudry & Willems \(forthcoming\)](#) show that optimistic bias in IMF GDP growth forecasts can induce subsequent economic contractions through higher accumulation of public and private debt. As the Covid19 pandemic raises the demand for IMF programs, improved nowcasts and an understanding which areas have produced nowcast inaccuracies are thus more important

⁶[Luna \(2014\)](#) also suggests that the IMF nowcasts may be overly optimistic because country authorities provided faulty data to the IMF; we could not find data to test this hypothesis. Another approach to explaining optimistic IMF forecasts bias are based on institutional factors that we also could not explore for lack of data. [Genberg & Martinez \(2014\)](#) find that the IMF desk economists with more years of experience make smaller forecast errors. [Beaudry & Willems \(forthcoming\)](#) find IMF mission chiefs' optimism systematically influences IMF forecasts.

⁷For MONA, [Baqir et al. \(2003\)](#) examines 29 program countries to find positive bias, as did [Baqir et al. \(2005\)](#) in a sample of 94. [Atoyan & Conway \(2011\)](#) examine fiscal and current account balances for 291 program countries and find positive forecast errors. [Luna \(2014\)](#) examines real GDP growth and inflation forecasts for 103 program countries and finds positive forecast bias for countries with “exceptional access to IMF resources”. Neither paper employs formal tests for bias/efficiency. [Genberg & Martinez \(2014\)](#) and [Timmermann \(2007\)](#) find optimistic bias in WEO.

than ever.

The remainder of the paper is organized as follows. Section II lays out the methodology, discusses the data, and provides first results. Section III establishes nowcast bias and/or inefficiency across relevant subsamples. Section IV examines why nowcasts have been inefficient and/or biased, and Section V investigates if nowcast efficiency changed. Section VI checks if time horizons affected nowcast accuracy and Section VII concludes.

II Evaluating Nowcasts: Data and Methodology

II.1 Data

Our nowcast data originates with the IMF’s Monitoring of Fund Arrangements (MONA) database ([IMF, 2020d](#)). The database reports the data that the IMF establishes at the time of crisis for 602 programs ranging from 1992 to today. Each program is identified by program-type⁸, approval date, and loan size. The database also reports macroeconomic indicators (in a highly unbalanced manner) for each program country, including three years of historical data that predates the crisis, t , the nowcast for t , and four additional years of forecasts. MONA also reports program conditionality, which the IMF groups into 9 categories of “quantitative” and 11 categories of “structural” (qualitative) performance criteria.⁹ Quantitative performance criteria reference numeric benchmarks (e.g., fiscal deficit targets) and structural performance criteria refer to policy and institutional reforms (e.g., income tax reform) that must be implemented by the program. We examine the MONA database’s nowcasts established in crisis year t for program year t . Since IMF projections are based on growth rates, we examine nowcasts for real/nominal GDP growth and inflation from $t-1$ to t . The MONA database also associates each program with Executive Board Documents which have become available in the IMF Archives since 2009. We review these documents in our MONA audit; the list of errors proved extensive (see Appendix A).

After each program starts, IMF economists review a country’s progress and enter estimates of realized data on a monthly, quarterly or semi-annual basis, depending on the program. EKPC used these subsequent reviews to obtain estimates of final outcome data for t . They accepted an estimate as final data if the review took place 18 months after a

⁸[IMF \(2020a\)](#) provides a full description of each of the 13 program-types which include Extended Credit Facility (ECF), Extended Fund Facility (EFF), Enhanced Structural Adjustment Facility (ESAF), Exogenous Shock Facility (ESF), Flexible Credit Line (FCL), Structural Adjustment Facility (SAF), Stand-By Agreements (SBA), Standby Credit Facility (SCF), Policy Coordination Instrument (PCI), Precautionary Credit Line (PCL), Precautionary Liquidity Line (PLL), Poverty Reduction and Growth Trust (PRGT), Policy Reform Instrument (PSI).

⁹See Table 1 for conditionality categories. Also see [IMF \(2020b\)](#) MONA database glossary.

program commenced. There are four reasons why this approach is unnecessarily restrictive and inaccurate. First, 48 programs do not have estimates of final data in MONA and were thus excluded by EKPC analysis although official final data exists. Second, the EKPC approach constrained the analysis to programs that lasted at least 18 months, omitting another 14 programs. Third, EKPC excluded another 106 programs due to unbalanced data or due to suspected database errors when observations exceeded four standard deviations from the mean. Fourth, MONA’s estimates of final data can differ substantially from the IMF’s official final data, which is reported in the IMF’s World Economic Outlook (WEO) database ([IMF, 2020f](#)). Figure 1 provides a visual representation of the differences between MONA’s estimated final data and WEO’ official final data for real GDP growth – only 57% of the data lie within 1% of each other. Differences between MONA’s estimated final data and WEO’s official final data thus contaminate EKPC’s assessment of nowcast accuracy, as errors in MONA’s estimated final data are attributed to nowcast inaccuracy. Below we evaluate IMF nowcast accuracy only on the basis of official final data obtained from the IMF’s WEO.

II.2 A Methodology to Evaluate Nowcast Accuracy

Forecast evaluation exercises generally focus on a range of forecast-error summary statistics that provide performance comparisons for different forecasts, for example, the mean absolute error (MAE) and the root mean square error (RMSE).¹⁰ Such statistics are informative only when two or more forecasts are being compared. The forecast evaluation in this paper involves, however, only a single forecast, since the IMF is the sole institution with access to country crisis data; this data remained confidential until 2009 when IMF Archives opened to the public. Hence we cannot hope to compare different nowcasts; we can only examine the accuracy of the solely available nowcast available at the time of crisis. The importance of these IMF nowcasts is thus derived directly from the fact that IMF nowcasters were in a unique position, enjoying exclusive access to confidential country data at the times of crises in order to design the loan programs.

The literature on forecast accuracy evaluation dates back to [Mincer & Zarnowitz \(1969\)](#), who based their analysis on the seminal work of [Theil \(1961\)](#). Theil introduced the concept of a “Prediction-Realization Diagram” as seen in Figure 2, which displays IMF nowcasts, F_t , on the horizontal axis. These IMF nowcasts are established at the time of crisis for the year in which the program was approved, t , for real/nominal GDP growth and inflation. Official final data, A_t , are plotted on the vertical axis. Mincer-Zarnowitz label the solid 45-degree line the “Line of Perfect Forecasts” as it represents coordinates where nowcasts

¹⁰A review of these statistics is provided by [Hyndman & Athanasopoulos \(2018\)](#)

equal official final data, $F_t = A_t$. For real GDP growth, the diagram indicates that IMF nowcasts overestimate low-growth recoveries and underestimate high-growth recoveries. A similar pattern exists for nominal GDP growth, but it is obscured by influential observations, which we further examine below. The white shaded area around the dashed regression line represents the 95% confidence interval.

Formally we can test whether nowcasts are unbiased and efficient using Mincer-Zarnowitz regressions, a methodology that has frequently been applied see e.g. [Romer & Romer \(2000\)](#), [Rossi & Sekhposyan \(2011\)](#), or [Granger & Newbold \(2014\)](#):

$$A_t = \alpha + \beta F_t + \varepsilon_t \quad (1)$$

where F_t are nowcasts and A_t are official final data. Nowcasts are chosen as the “independent” variable only because they are available before the official final data is published. A forecast is efficient when the forecast error, ε_t , is uncorrelated with the forecast. In this case, the slope parameter, β , in (1) is unity and the residual variance of the regression equals the variance of the forecast error. To test the accuracy of forecasts, Mincer-Zarnowitz suggest the joint null hypothesis $\alpha = 0$ & $\beta = 1$ to see if forecasts are optimal in that they are unbiased and efficient. Since the estimates of α and β are generally correlated, the individual T statistics provide inappropriate tests and the joint test is required ([Wallis, 1989](#)).

If the Mincer-Zarnowitz null ($\alpha = 0$ & $\beta = 1$) is rejected, nowcasts are inefficient but they may or may not be biased. [Holden & Peel \(1990\)](#) subsequently derived a necessary and sufficient condition for unbiased nowcasts, which simply tests whether the regression line intersects the Line of Perfect Forecasts at their respective expected values $E(A_t) = E(F_t)$. When [Holden & Peel \(1990\)](#) test of $A_t - F_t = \gamma + v_t$ rejects the null of $\gamma = 0$, the nowcast is said to be biased. Here it is important to note that this notion of bias implies that nowcasts exhibit no bias at all when they are half of the time 20% higher and half of the time 20% lower than the official final data. This is why Mincer-Zarnowitz stress that unbiasedness is desirable, but not by itself informative about forecast accuracy. Of course, other things being equal, the smaller the bias, the greater the accuracy of the forecast; “other things” here being the distances between the points in the prediction-realization diagram and the Line of Perfect Forecasts. These distances can be expressed by the variance of the forecast error around its mean, which Mincer-Zarnowitz introduce as an inverse measure of forecast efficiency. Rotations of regression lines to better match Lines of Perfect Forecasts reduce this variance to increase efficiency.

A nowcast is inefficient when it does not incorporate all information that is available at the time the nowcast is established. That is why [Nordhaus \(1987\)](#) noted that the concept of

forecast efficiency shares similarity with the concept of stock market efficiency – both imply that efficiency exists when all relevant and available information was considered. Even if the Holden Peel test indicates unbiased forecasts, the slope coefficient, β , in (1) may indicate a statistically significant deviation from unity to suggest inefficiency.

Regressions (2a)-(2c) in Table 2 are Mincer-Zarnowitz regressions associated with Figure 2 for real/nominal GDP growth and inflation. In regressions (1a)-(1c) we revisit the results in EKPC that were based on their sample of 110 of the available 602 programs. EKPC rejected efficiency but not, on average, bias.¹¹ In regressions 2a)-2c) we add the programs EKPC omitted, include programs for the additionally available years (1992-2001), and use official, not estimated, final data as in EKPC.

Real GDP growth nowcasts are inefficient but unbiased in EKPC and in our full sample. Slope coefficients are significantly below unity, suggesting low (high) growth recoveries are over (under) estimated. Nominal GDP growth is unbiased and efficient in EKPC, but the inclusion of our additional data eliminates efficiency. We find a much smaller slope coefficient in the Mincer-Zarnowitz regression that is statistically significant from unity. The intercept is also significantly larger than zero, suggesting that IMF nominal GDP growth nowcasts over (under) estimate low (high) growth recoveries, as was the case for real GDP growth. Inflation shows the greatest divergence in results. EKPC found near perfect, unbiased and efficient IMF inflation nowcasts with near unitary slope and zero intercept, suggesting that nowcasts closely match the Line of Perfect Forecasts. When we include the previously omitted programs, as well as official (not estimated) final data, we find that IMF inflation nowcasts exhibit statistically significant bias and inefficiency. As was the case for GDP growth, IMF nowcasts for inflation over (under) estimate low (high) growth recoveries.

The fact that low GDP growth crisis recoveries are overly optimistically nowcast in the full sample presents major problems for IMF crisis program countries. First, overly optimistic nowcasts for low-growth recoveries may imply an underestimate of the loan requirements and of the quantitative and structural adjustment needs. On the other hand, overly pessimistic nowcasts for the high-growth recoveries overstate programs' financial needs, which may lead to misallocation of resources. Second, overly optimistic nowcasts can translate into overly optimistic program targets and performance criteria (e.g., government revenues or import volumes) that may actually be more difficult or impossible to reach. Third, overly optimistic nowcasts for low-growth recoveries affect program evaluations, as below-par program performance may, in fact, only be due to excessively optimistic nowcasts.

¹¹In contrast to EKPC we do not include regional or crisis dummies in the benchmark; the inclusion of such dummies invalidates the Mincer-Zarnowitz null hypothesis. The question of whether IMF nowcasts do not properly integrate regional or global crisis information in is examined in Section IV.

III Does Nowcast Bias and Efficiency Vary by Subsample?

Figures (2b)-(2c) suggest that the assessment of IMF nowcast accuracy may be impacted by influential observations, likely relating to nowcast inaccuracies in high inflation countries. Below we examine whether IMF nowcast accuracy differs by subsamples, specifically subsamples that differ by income and inflation. We use the common World Bank Low-Income Country (LIC) demarcation¹², and for inflation we use [Dornbusch & Fischer \(1986\)](#) threshold of inflation $> 25\%$ to identify hyperinflation crises. Note that our hyperinflation sample is best described as a sample of anticipated hyperinflation countries, since we code countries for hyperinflation only if IMF nowcasts forecasted hyperinflation. In that sense, hyperinflation was not a surprise to IMF forecasters, they already predicted it in their nowcasts. Hence we evaluate only how accurate IMF nowcasts are for countries and crises for which the IMF expected hyperinflation.¹³

Separating the samples by hyperinflation and LICs, we obtain the subsample prediction-realization diagrams in Figure 3, suggesting a substantially improved fit and nowcasts for the Non-Hyperinflation & Non-LICs subsample as compared to Figures (2a)-(2c). Table 3 reports Mincer-Zarnowitz regressions for the subsamples. For real GDP growth, nowcast accuracy differs substantially across subsamples. The full sample, the Non-Hyperinflation sample, and the LICs sample are all inefficient. Efficiency arises only once we purge the full sample of LICs and hyperinflation nowcasts. This implies that the inefficiency in the full sample is driven by nowcasts for hyperinflation countries and LICs.

The slope coefficients are below unity for all subsamples, indicating overly optimistic nowcasts for low real GDP growth recoveries and overly pessimistic estimates for high-growth recoveries. This effect is greatest for Non-Hyperinflation LICs with an astonishing low β of 0.6, indicating enormous improvement potential for IMF nowcasts for this subsample of 276 programs. By calculating the intersection between the regression line in (1) and the Line of Perfect Forecasts, we find that fragile Non-Hyperinflation LICs, those with below 5% real GDP growth recoveries, may have been impacted by conditionality and performance evaluations that were based on excessively optimistic IMF crisis assessments.

Surprisingly, IMF real GDP growth nowcasts for hyperinflation countries are not statistically significantly biased or inefficient. This is likely an artifact of the high variance in the official final data for hyperinflation countries (see Table 3), which is twice the magnitude

¹²Low-Income Country classification is a time-varying measure based on World Bank's data of GNI per capita in each year. See databank.worldbank.org/data/download/site-content/OGHIST.xls

¹³If hyperinflations or even just the events leading up to hyperinflations were a surprise to IMF forecasters (and hence not part of their information set) we would not want to link such surprises to IMF nowcast bias and inefficiency.

of other subsamples variances. High variance outcomes are harder to forecast, resulting in substantially larger forecast errors, as reported in Table 3. The large standard errors in the hyperinflation subsample then widen the confidence bands to the point where the Mincer-Zarnowitz F-test cannot rule out that intercept and slope coefficients are consistent with the Line of Perfect Forecasts (see Figure 3.3a). It is important, however, to note that the vast majority (55%) of hyperinflation events occurred in the very early part of the sample, before 1997. In that sense, the noise introduced by hyperinflation forecast errors is not representative of ongoing nowcast dynamics over the years in the full sample. This is in contrast to the effects of LICs nowcast errors whose contribution to the full sample inefficiency is steady over the 28 year time period.

For nominal GDP growth in hyperinflation countries, we find a pattern similar to what we observed for real GDP growth. In the full sample the slope coefficient is substantially below unity, and Table 3 shows that this result is driven entirely by nowcast inaccuracies for hyperinflation countries. The slope coefficient of hyperinflation nowcasts is substantially below unity at 0.666. This indicates again that IMF nowcasts substantially overestimate nominal GDP growth in “low hyperinflation” recoveries (smaller than 18.6%) and underestimate nominal GDP growth in “high hyperinflation” recoveries. Once we purge the full sample of hyperinflation countries, we find slope coefficients near unity across subsamples (ranging from 0.987 to 1.052), indicating efficient nowcasts.

Interestingly, both the Non-Hyperinflation and the Non-Hyperinflation LICs subsamples exhibit biased nominal GDP growth nowcasts. This is because the positive intercept together with high slope coefficients imply that biased overestimates and biased underestimates cannot average out. Here it is important to note that the bias is driven entirely by LICs. Once LICs are removed from the Non-Hyperinflation sample, the slope is just about unity (1.05) and nowcasts are unbiased and efficient. In summary, for nominal GDP growth we find that the full sample must be exclude (i) hyperinflation countries to achieve efficiency, and (ii) LICs to achieve unbiased nowcasts.

Inflation nowcasts produce the largest accuracy variations across subsamples. Biased and inefficient nowcasts are observed for the full sample, the Non-Hyperinflation sample and the Non-Hyperinflation LICs samples. As in the case of nominal and real GDP growth, once we purge the full sample of Hyperinflation and LICs programs, nowcasts become efficient and unbiased. Slope coefficients are high and exceed unity for Non-Hyperinflation samples (LICs or Non-LICs), indicating that, for Non-Hyperinflation countries, IMF nowcasts underpredict inflation for low inflation recoveries (smaller than 1.7%) and over predict inflation for high inflation events. Only the Hyperinflation subsample exhibits a slope coefficient that is below unity, indicating that IMF nowcasts decisively overestimate “low hyperinflations” and

underestimate “high hyperinflations.”

The important finding of the subsample analysis is that we can document Non-Hyperinflation Non-LICs programs (about 42% of the sample) exhibit unbiased and efficient nowcasts for real and nominal GDP growth and for inflation. Hyperinflation countries contribute to bias and inefficiency, but given that their numbers are concentrated in a few early years in the 28-year sample, the real driver of bias and inefficiency in the full sample are thus Non-Hyperinflation LICs. The analysis raises the question as to the drivers of inefficiency and/or bias, which we explore in the next section.

IV Why Are IMF Nowcasts Inefficient?

[Sinclair, Joutz, & Stekler \(2010, SJS\)](#) and [Sinclair, Stelder, & Caraow \(2012\)](#) propose a methodology to investigate potential sources of forecast inefficiencies. They suggest including additional covariates in (1) that represent information which was available to forecasters at the time of the forecast.

$$A_t = \alpha + \beta F_t + \delta X_t + \varepsilon_t \quad (2)$$

where X_t are additional candidate covariates known to forecasters at time, t . SJS propose the joint null hypothesis of $\beta = 1$ & $\alpha = \delta = 0$ to identify whether the information content of the additional covariates is properly included in the nowcast. If the null is rejected, SJS note that the information contained in X was not fully integrated into the nowcast, identifying a possible source of inefficiency.

We examine eight groups of candidate covariates to test whether they were properly accounted for in IMF nowcasts, specifically, (i) international crises, (ii) regions, (iii) conditionality (quantitative and structural performance criteria), (iv) program objectives, (v) loan amount and loan cancellation, (vi) elections, (vii) conflicts, and (viii) natural disasters to see if nowcasts properly account for their effects.

Two international crises occur in the time period of our data: the 1997 Asian Crisis and the 2008 Global Financial Crisis. The effects of these international crises were not country-specific, and one might suspect that international contagion and crisis spillovers may not have been fully integrated into IMF nowcasts for individual program countries. [Genberg & Martinez \(2014\)](#) and [IMF-IEO \(2014\)](#) find that IMF WEO forecasts tend to be consistently over-optimistic with larger forecast errors in times of regional and global recessions, and the Asian and Global crises represent two such cases. Here it is important to emphasize that we are examining only sources of inefficiencies based on information available to IMF forecasters at the time of the nowcast. Hence our crisis dummies are set to one only for countries whose

programs started after the two international crises commenced.¹⁴ Regional effects proxied by Africa, Asia, and Latin American dummies, which commonly hold explanatory power in growth regressions (see, e.g., [Barro \(1991\)](#) and [Masanjala & Papageorgiou \(2008\)](#) for Africa, and [Fernandez et al. \(2001\)](#) for Asia and Latin America).

Another set of regressors we investigate as possible sources of inefficiencies relates to IMF conditionality. Conditionalities are specifically designed to affect program countries' recoveries, hence nowcasts must exercise particular caution to integrate their effects. For example, conditionality often relates to fiscal discipline and credit targets that directly affect GDP growth and/or inflation. Conditionality comes in two flavors: "quantitative performance criteria" (QPC, e.g., "dollar ceiling on external debt") and "structural performance criteria" (SPC) which refer to policy reforms. The IMF MONA database groups conditionalities into 9 categories of QPCs and 11 categories of SPCs that we add to regression (1).¹⁵

The IMF offers countries a menu of program-types to focus recoveries on different aspects of an economy. Program types address a wide range of issues from external financing difficulties to non-financial reforms, and poverty/growth.¹⁶ We examine if the differential focuses of program types have been fully accounted for by IMF nowcasts. In addition, the previous literature on IMF program performance also noted the importance of program-loan size (e.g., [Dreher \(2006\)](#)). [Luna \(2014\)](#) also notes that exceptional access to fund resources imposed particular optimistic bias. Hence, we also examine whether the approved loan size relative to IMF quota¹⁷ is fully accounted for in IMF nowcasts.¹⁸ [Atoyan & Conway \(2011\)](#), [Luna \(2014\)](#), and [IMF \(2019\)](#) all point out that all IMF program forecasts are conditional on the assumption of successful implementation of quantitative and structural reform targets so that failures to implement could contribute to optimistic bias of forecasts. We examine ex-post effects of cancelled programs on nowcast bias and efficiency and found they did not

¹⁴The 1997 Asian Crisis dummy received a "1" for programs that (i) commenced between 7/2/1997 and 1/1/1999, and (ii) that were identified as affected Asian Crisis Countries by [Kaminsky et al. \(2003\)](#). In July 1997, Thailand was forced to float its exchange rate, which is generally seen as the start of the crisis. The 2008 Global Financial Crisis dummy received a "1" for programs that commenced between 9/15/2008 and 9/15/2009, where the start date is the Lehman Brothers' bankruptcy filing date.

¹⁵See Table 1 for details.

¹⁶We grouped the 13 IMF programs types into 5 program objectives:

- (i) BOP Stabilization: Stand-By Agreements (SBA);
- (ii) BOP Shocks: Exogenous Shock Facility (ESF), Standby Credit Facility (SCF), Flexible Credit Line (FCL), Precautionary Credit Line (PCL), Precautionary Liquidity Line (PLL);
- (iii) Structural Adjustment Poverty Reduction And Growth: Structural Adjustment Facility (SAF), Enhanced Structural Adjustment Facility(ESAF), Poverty Reduction and Growth Trust (PRGT);
- (iv) Non-Financial Reforms: Policy Reform Instrument (PSI), Policy Coordination Instrument (PCI);
- (v) Long-Term BOP Reforms: Extended Credit Facility (ECF), Extended Fund Facility (EFF).

¹⁷The quota data is from the IMF International Financial Statistics database ([IMF, 2020c](#)).

¹⁸The result is similar if replace the approved loan size with actually drawn loan size.

affect results.¹⁹

Finally, we examine a block of non-economic regressors that may well exert profound effects on the economy, including elections, conflicts (civil and international), and natural disasters. In its review of program design and conditionality ([IMF, 2019](#)) noted that forecast errors of program countries are impacted by political transitions, conflicts, and natural disasters. Again we are asking if knowledge of such non-economic factors was properly integrated into the nowcasts. The noneconomic dummies exhibit a one only if the event occurred before the program was approved, so that IMF nowcasters were well aware of the events and their effects on GDP growth and inflation.²⁰

IV.1 Sources of Nowcast Inefficiency in the Full Sample

Table 4 regressions (4.1.a)-(4.3.c) display GDP growth and inflation results for the three key subsamples. We start by discussing the full sample results. For real GDP growth (regression 4.1.a) the null hypothesis that nowcasts could not have been improved by the consideration of additional variables (SJS F-test) is rejected at the 10% level. However, only four covariates are so marginally significant that we don't list them here, reflecting that the initial nowcast was unbiased and efficient.

In contrast, for nominal GDP growth in the full sample, the SJS F-test is rejected at the 1% level (regression 4.2.a), indicating that IMF nowcasts could have been improved if the effects of regions (America) and the effects of the 2008 financial crisis had been properly considered. In addition, there is strong evidence that several conditionality dimensions were also not properly integrated into IMF nominal GDP nowcasts in the full sample. These dimensions include quantitative performance criteria relating to a) reserves, b) external arrears, c) fiscal deficit, d) external debt, and structural performance criteria relating to current/capital account restriction. In addition, nominal GDP growth nowcasts could have been improved through better consideration of the implications of program types that address balance of payments stabilization problems (SBA programs) and poverty reduction growth (ESAF, SAF, and PRGF programs).

For inflation, the SJS F-test in the full sample is rejected at the 5% level (regression 4.3.a), indicating that the efficiency of IMF nowcasts could have been improved through the

¹⁹Results can be obtained from the authors upon request.

²⁰Table 1 provides elections, conflicts, and disasters details. Election dummy covers (i) head of state/government elections and (ii) legislative elections. Programs received a “1” if elections occurred up to 1 year prior to program start; see [Beck et al. \(2001\)](#) and [IFES \(2020\)](#). Conflict dummy covers intra/inter-state conflicts. Programs received a “1” if (civil) wars occurred up to 1 year prior to program start; see [Harbom et al. \(2009\)](#). Disaster dummy covers natural disasters. Programs received a “1” if disasters occurred up to 1 year prior to program start; see [EM-DAT \(2020\)](#).

consideration of additional covariates such as the effect of 2008 Global Financial Crisis and conditionality. Specifically, the effects of quantitative targets on government and central bank credit were not properly integrated into IMF nowcasts. In addition, inflation nowcasts could have been improved through consideration of the effects of structural reforms in economic statistics, trade openness, and state enterprises. As in the case of nominal GDP growth, the effects of balance of payments stabilization programs were also not properly accounted for by IMF inflation nowcasts.

In summary, for the full sample, the effects of the 2008 Global Financial Crisis are the only common factors that were not properly accounted for by IMF nowcasts for GDP growth and inflation. As indicated by the statistically significant crisis coefficient, which is negative across GDP growth and inflation, the IMF nowcasts produced overly optimistic estimates of recoveries during the crisis as previously observed by Genberg and Martinez (2014). In addition, each nowcast has additional distinct factors that were not fully integrated into the nowcasts and whose proper consideration would have improved efficiency. Since we learned in the previous section that the inefficiency of the full sample is decisively driven by inefficiencies in the Non-Hyperinflation LICs sample (and to a lesser extent by early hyperinflation), we examine effects of additional covariates for these two subsamples in Table 4.

IV.2 Sources of Nowcast Inefficiency in the Non-Hyperinflation LICs Sample

In Table 4, regressions (4.1.b)-(4.3.b) also indicate that the efficiency GDP growth and inflation nowcasts for Non-Hyperinflation LICs could have been improved. Real GDP growth nowcast inefficiency (regression 4.1.b) was driven by overestimates of growth during the 1997 Asian Crisis, as indicated by the negative coefficient. Additional factors whose consideration could have improved efficiency were reforms of labor and financial markets, as well as the economic effect of elections. For nominal GDP growth, nowcasts efficiency could have been improved if quantitative limit on fiscal deficits, reforms of current/capital accounts and program type (BOP Stabilization, SBA) had been fully integrated. Inflation nowcasts could have been improved through better integration of the effects of quantitative restrictions on reserves, trade reforms and non-financial reforms along with effects of the poverty and growth programs and the 2008 crisis.

IV.3 Sources of Nowcast Inefficiency in the Hyperinflation Sample

For hyperinflation countries, there is perhaps the strongest evidence that inefficient real/nominal GDP growth and inflation nowcasts could have been improved. For real GDP growth, we find three highly statistically significant factors that should have been properly integrated:

quantitative limits on government credit and deficit, as well as limits on external debt and central bank credit. In terms of structural reforms, we find evidence (regression 4.1.c) that state enterprise reform and central bank statistical/regulatory reforms could have improved the nowcasts. Even the effect of elections is now indicated as a factor that could have improved the nowcasts. For nominal GDP growth nowcasts in hyperinflation countries, the most important factors that could have improved the nowcast were nonfinancial reforms and program type (Balance of Payment Stabilization, SBA). In addition, reforms of public employment and current/capital account openness are statistically significant. For inflation nowcasts, the SJS test is also rejected at the 1% level and the ceiling on central bank credit could have improved efficiency.

V Did Nowcast Bias and Efficiency Change Over Time?

Our MONA nowcast data covers over a quarter century of IMF programs. It is natural to ask whether the accuracy of nowcasts changed over time. It may well be that the advent of better models and improved data collection produced successively better nowcasts. Instead of reporting nowcasts accuracy for each individual year, we report results for rolling 5-year periods. This allows us to keep the number of observations per period roughly similar and of sufficient size.

Figure 4.1 provides visuals of nowcast accuracy over time for the full sample, using Mincer-Zarnowitz regressions that are reported in Appendix Table B.1. The black line in Figure 4.1 is the value of the β estimates in Table B.1 and the dotted lines represent 95% confidence intervals. We observe four distinct periods. First, all nowcasts struggled with bias and/or inefficiency until about 2001. Second, all nowcasts saw a reprieve with unbiased and efficient nowcasts until 2005. Third, another period of bias and/or inefficiency occurred until 2009 (2012 for real GDP growth). Fourth, after 2012, GDP growth nowcasts become unbiased and efficient (with one exception in 2013), but inflation nowcasts continue to struggle with efficiency as recently as 2018. It is fascinating to see that inflation still struggles with inefficiency in recent years while nominal GDP growth nowcasts have become efficient.

In addition to our assessment of nowcast accuracy, we observe that the slope coefficients for nowcasts, β , is almost always smaller than unity until 2014. This implies a long-enduring pattern of overly optimistic nowcasts for low-growth countries, and overly pessimistic nowcasts for high-growth countries. The pattern reverses after 2015 when the slope coefficients start to exceed unity for both inflation and real GDP growth. This suggests that since about 2015 IMF nowcasts become excessively pessimistic (optimistic) for low (high) growth out-

comes. We also note that the width of the error bands indicates that the standard errors are roughly similar throughout. The exception is real GDP growth, which experienced a widening of the confidence interval during the 2008 Global Financial Crisis (producing inefficient nowcasts). Nominal GDP growth exhibits extraordinarily large errors in the early 1990s and also during the financial crisis. Inflation bucks the trend with tight standard errors until 2007 and stable error bands for the remaining years.

Above we noted the importance of two subsamples in our study of bias and inefficiency: especially Non-Hyperinflation LICs introduced forecasts errors that translated into nowcast inaccuracy for the full sample. Given the results above, we are also interested in this subsamples' pattern of nowcast accuracy over time. Even though the hyperinflation sample contains 76 observations, it is too concentrated in the early years of our 28-year sample period, rendering too few observations to produce meaningful 5-year rolling time periods throughout.

For the Non-Hyperinflation LICs sample (Figure 4.2) we find a roughly similar pattern to for the full sample, in that earlier nowcasts are more likely to be inefficient and later nowcasts (since 2014) have become unbiased and efficient for GDP growth. Even inflation is unbiased and efficiently nowcast in the Non-Hyperinflation LICs sample in recent years. This is good news, especially given the nearly unbroken string of biased and/or inefficient nominal GDP growth nowcasts in this sample from 2001–2013.

VI Did Nowcast Horizons Affect Nowcast Accuracy?

In general, forecast accuracy is expected to decrease as forecast horizons increase (Armstrong 2001). This may be expected to be particularly relevant for IMF nowcasts, as information sets are larger at the end of the year due to the accumulation of several data vintages over the year. Hence, one might well expect nowcast bias and efficiency to improve for programs designed and approved later in the year. In this section we examine whether bias and inefficiency is driven by nowcast horizons. Figure 5 provides the visual summary of results for the full sample, and the regression outputs are reported in Appendix Table B.3. We examine whether nowcasts produced earlier in the program year exhibit a greater propensity towards bias and inefficiency than those formed later in the year.

The results are surprising, as there is no clear pattern of improved nowcast accuracy when the time horizon shortens. Both real GDP growth and inflation nowcasts exhibit greater variances early in the year, but these do not necessarily translate into greater bias and/or inefficiency. Indeed, real GDP growth and inflation poignantly produce inefficient and even biased nowcasts later in the year. Surprisingly, inflation nowcasts are the most stable around

the slope parameter of unity throughout the year, while nominal GDP growth produces the largest deviations from unity. This could be due to the fact that inflation information is much more readily available (on a monthly basis) than GDP growth (at best quarterly). The divergence in GDP growth and inflation accuracy as the time horizon shortens also implies that GDP growth nowcast errors are not driven by inflation nowcast errors. This finding is supported by the fact that there is no similarity in the pattern of real GDP growth nowcast inaccuracies and either inflation or nominal GDP growth nowcasts.

Biased and inefficient nowcasts are found mid-year in April and May and somewhat surprisingly at the end of the year in November when nowcasts turn excessively optimistic. Nominal GDP growth has the expected bias and inefficiency in January but the next two months are both unbiased and efficient with four additional inefficiencies throughout the year. For inflation, bias is again early in the year but bias and inefficiencies are concentrated mid-year. Overall we see no pattern of either bias and efficiency improving over the year. [IMF-IEO \(2014\)](#) previously found evidence that IMF forecast errors increase with time horizons in WEO data, but their study horizons far exceeded the time period covered in this paper.

VII Conclusion

IMF nowcasts established at the time of crisis are the basis for IMF program conditions for countries that request assistance from the lender of last resort. Instead of examining the IMF program efficacy, we formally examine the accuracy of the nowcasts that predicate IMF program design in a dataset that is six times larger than the largest previous study on the subject. We find that GDP growth (real and nominal) and inflation nowcasts are inefficient in the full sample, a result driven by substantial bias and inefficiency in Low-Income Countries (LICs). We show that these inaccuracies are not a function of the nowcast horizon, and document that GDP growth nowcasts have improved in recent years. In contrast, inflation nowcasts continue to struggle with accuracy until recently.

Instead of documenting the uniform optimism in IMF forecasts, which has largely been accepted as a stylized fact in the previous literature, we dissect the structure of nowcast bias and inefficiency and highlight that only the most vulnerable, low-growth recovering LICs are subject to excessively optimistic forecasts. Nowcasts for fast-growing countries are actually excessively pessimistic, underestimating the speed of the recovery. Once purged of LICs, the remaining sample actually exhibits no statistically significant optimistic/pessimistic bias. Our findings have important implications for LICs crisis countries. IMF conditionality based on overly optimistic nowcasts may affect the likelihood that the country can achieve the conditions, and affect future loan disbursements and program evaluation. In addition, the

forecast bias may produce quantitative performance targets that are impossible to reach. As the Covid19 pandemic has raised the demand for IMF programs, improved nowcasts are thus more important than ever.

The dichotomy between countries that are optimistically or pessimistically assessed raises the question regarding the drivers of the inefficiency in IMF nowcasts. We investigate the sources of nowcast inefficiencies by country subsamples to highlight the factors that were in the IMF forecasters' information sets, but were improperly integrated into nowcasts. Each type of forecast (GDP/Inflation) and each subsample of countries (Full/LICs/Hyperinflation) produces a different set of conditions and program types that were improperly integrated into IMF forecasts. Our work has been made possible through the merger of several IMF databases as well as a comprehensive audit of the data, which was found to include an inordinate amount of errors in the public IMF database. This is noteworthy, since the databases are the basis of a substantial number of research papers.²¹

²¹A quick search produces over 2000 papers that have been published on the basis of the IMF MONA Database. Results of our audit and corrected errors are documented in Appendix A.

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Table 1: Variables

Variable	Data Source	Description
IMF Nowcasts	IMF (2020d) MONA Database. See Appendix A for details	"t-1" to "t" period growth rates for real GDP levels (RGDPC/NGDP_R), nominal GDP levels (NGDP), end-of-period inflation (PCPIC/PCPIE)
Final Realized Data	IMF (2020f) WEO Database	"t-1" to "t" period growth rates for real GDP levels (NGDP_R), nominal GDP levels (NGDP), end of period inflation (PCPIE)
2008 Crisis		Dummy variable for the 2008 Global Financial Crisis. Program received a "1" when program commenced between 9/15/2018 and 9/15/2019. The start date of 2008 crisis is the Lehman Brothers' bankruptcy filing date.
2007 Crisis		Dummy variable of the 1997 Asian Crisis. Program received a "1" for programs that commenced between 7/2/1997 and 1/1/1999; and (ii) the country was also identified as an Asian Crisis Country by Kaminsky, Reinhart, and Vegh (2003). In July 1997, Thailand was forced to float exchange rate, which is generally seen as the start of the crisis.
Regions		Dummy variables for Africa, Americas, Asia, and Europe.
Conditionality: QPCs	IMF (2020b) MONA Database Glossary	Dummy variables given by MONA's "Main Criteria" defined by MONA Glossary .
Conditionality: SPCs	IMF (2020b) MONA Database Glossary	Dummy variables given by MONA's "Indicative Targets" defined by MONA Glossary. We grouped them as: Gen_Gov't_Reform (1.1-1.9), CB_Stats_Regs_Indep.(2.1-2.2), Civil_Service_Wage/Empl. (3), Pension_Reform (4.1-4.2), Gov't_Enterprise_Pricing (5.1-5.3), Financial_Sector_Reform (6.1-6.2), Open_Current&Capital_Account (7), Reduce_Trade_Tariff/Quota (8), Labor_Mkt_Wage/Empl.(9), Improve_Econ_Statistics (10), Legal/Market_Reforms (11.1-11.4)
Program Objectives	IMF (2020a) Crisis Lending Fact Sheet	We grouped IMF loan types into 5 broad categories: (i) BOP_Stabilization: Stand-By Agreements (SBA); (ii) BOP_shocks_precautionary: Exogenous Shock Facility (ESF), Standby Credit Facility (SCF), Flexible Credit Line (FCL), Precautionary Credit Line (PCL), Precautionary Liquidity Line (PLL); (iii) Struct_Adj_Poverty_Growth: Structural Adjustment Facility (SAF), Enhanced Structural Adjustment Facility(ESAF), Poverty Reduction and Growth Trust (PRGT); (v) long-term BOP and structural reform assistance: Extended Credit Facility (ECF), Extended Fund Facility (EFF) (iv) Non_Financial_Reforms: Policy Reform Instrument (PSI), Policy Coordination Instrument (PCI);
LoanAmount	IMF (2020d) MONA Database for loan amount drawn, IMF (2020c) IFS Database for quota	Loan Amount is the ratio of drawn loan size to IMF country annual quota in the program start year.
Elections	Beck et al (2001) for data before 1998; IFES (2020) for post 1998 data	Election dummy cover two types of national elections: (i) head of state or government election; (ii) legislative election. Program received a "1" if an election occurred up to 1 year prior to the program start date.
Conflicts	UCDP/PRIOR Armed Conflict Dataset by Harbom et al. (2009)	Conflict dummy covers intra-state and inter-state conflicts. Program received a "1" if program country experienced a conflict up to one year prior to program start date.
Disasters	EM-DAT (2020)	Disaster dummy covers natural disasters. Program received a "1" if a disaster occurred up to 1 year prior to the program start date.

Table 2: Bias and Inefficiency of IMF Nowcasts

Dependent Variable:	Actual RGDP Growth		Actual NGDP Growth		Actual Inflation	
	(1a)	(2a)	(1b)	(2b)	(1c)	(2c)
	EKPC (2019)	Full dataset	EKPC (2019)	Full dataset	EKPC (2019)	Full dataset
Constant, α	0.016**	0.004	0.014*	0.062***	0.002	0.038***
p-value ($\alpha=0$)	0.013	0.206	0.071	0.000	0.875	0.003
IMF Nowcast, β	0.621***	0.821**	0.926	0.666***	1.091	0.864
p-value ($\beta=1$)	0.010	0.044	0.193	0.000	0.702	0.185
Observations	110	597	110	596	100	595
Adjusted R-square	0.402	0.404	0.742	0.836	0.545	0.810
MZ F-test ($\alpha=0, \beta=1$)	3.460**	2.731*	1.740	13.93***	1.021	8.258***
p-value ($\alpha=0, \beta=1$)	0.035	0.066	0.180	0.000	0.364	0.000
HP T-test ($\gamma=0$)	-0.111	-1.464	1.180	-0.946	1.408	2.595**
p-value ($\gamma=0$)	0.912	0.144	0.240	0.344	0.162	0.010

Note:

- (1) Robust standard errors in parentheses unless otherwise indicated; *** p<0.01, ** p<0.05, * p<0.1
- (2) Mincer Zarnowitz Null: Nowcast is unbiased and efficient
- (3) Holden Peel Null: Nowcast is unbiased

Table 3: Nowcast Accuracy by Subsample

Dependent Variable:	RGDP Growth					NGDP Growth					Inflation								
	(1)		(2)		(3)	(4)		(5)		(1)		(2)		(3)		(4)		(5)	
	All	Non-Hyper	Non-Hyper LICs	Non-Hyper Non-LICs	Hyper Inflation	All	Non-Hyper	Non-Hyper LICs	Non-Hyper Non-LICs	Hyper Inflation	All	Non-Hyper	Non-Hyper LICs	Non-Hyper Non-LICs	Hyper Inflation				
Constant, α	0.004	0.008**	0.020***	0.003	-0.008	0.062***	0.003	0.011	-0.004	0.188***	0.038***	-0.004	0.002	-0.010	0.197***				
p-value ($\alpha=0$)	0.206	0.010	0.001	0.390	0.234	0.000	0.704	0.520	0.665	0.000	0.003	0.658	0.929	0.168	0.001				
IMF Nowcast, β	0.821**	0.775***	0.601***	0.835	0.801	0.666***	1.02	0.987	1.052	0.624***	0.864	1.242	1.262	1.210	0.792**				
p-value ($\beta=1$)	0.044	0.002	0.001	0.145	0.437	0.000	0.798	0.919	0.551	0.000	0.185	0.156	0.407	0.129	0.023				
Observations	597	526	276	250	71	596	525	276	249	71	595	526	275	251	69				
Adjusted R-square	0.404	0.353	0.155	0.486	0.383	0.836	0.665	0.625	0.699	0.834	0.810	0.309	0.207	0.595	0.822				
MZ F-test ($\alpha=0$ & $\beta=1$)	2.731*	4.841***	5.685***	1.362	0.988	13.93***	1.685	2.039	0.202	11.26***	8.258***	6.062***	6.222***	1.190	5.8***				
p-value ($\alpha=0$ & $\beta=1$)	0.066	0.008	0.004	0.258	0.377	0.000	0.186	0.132	0.818	0.000	0.000	0.003	0.002	0.306	0.005				
HP T-test ($\gamma=0$)	-1.464	-0.882	-0.345	-1.001	-1.334	-0.946	1.757*	1.834*	0.508	-1.525	2.595**	2.997***	2.692***	1.345	1.135				
p-value ($\gamma=0$)	0.144	0.378	0.730	0.318	0.187	0.344	0.079	0.068	0.612	0.132	0.010	0.003	0.008	0.180	0.260				
St Dev: Actual Data	0.050	0.043	0.040	0.042	0.077	0.426	0.137	0.141	0.129	1.051	0.382	0.122	0.145	0.089	0.893				
St Dev: Forecast Error	0.039	0.035	0.038	0.031	0.062	0.261	0.079	0.086	0.071	0.718	0.175	0.102	0.130	0.058	0.430				
MAE	2.457	2.264	2.406	2.108	3.882	7.202	4.747	5.285	4.150	25.355	6.482	4.512	5.789	3.111	21.506				
RMSE	3.914	3.496	3.838	3.075	6.186	26.089	7.953	8.660	7.088	72.427	17.579	10.286	13.107	5.787	43.108				

Note:

- (1) Robust standard errors in parentheses unless otherwise indicated; *** p<0.01, ** p<0.05, * p<0.1
- (2) Mincer Zarnowitz Null: Nowcast is unbiased and efficient
- (3) Holden Peel Null: Nowcast is unbiased
- (4) MAE (mean absolute error), RMSE (root mean square error), are scaled by 100

Table 4: Sources of Nowcast Inefficiency by Subsamples

		Real GDP Growth			Nominal GDP Growth			Inflation		
		(4.1.a)	(4.1.b)	(4.1.c)	(4.2.a)	(4.2.b)	(4.2.c)	(4.3.a)	(4.3.b)	(4.3.c)
		Full Sample	Non-Hyper LICs	Hyper Inflation	Full Sample	Non-Hyper LICs	Hyper Inflation	Full Sample	Non-Hyper LICs	Hyper Inflation
Constant, α		-0.007	-0.035	0.084**	0.034	-0.099	-0.008	0.037	-0.155	0.176
p-value ($\alpha = 0$)		0.533	0.491	0.050	0.336	0.161	0.982	0.553	0.124	0.609
IMF Nowcast, β		0.764*	0.558***	0.946	0.649***	0.947	0.630***	0.837*	1.122	0.802**
p-value ($\beta = 1$)		0.015	0.003	0.673	0.000	0.699	0.001	0.082	0.688	0.011
2008 Crisis		-0.013*	0.007	-0.022	-0.046***	-0.053	0.323	-0.035*	-0.068*	1.370
(0.007)	(0.015)	(0.046)		(0.014)	(0.033)	(0.292)		(0.021)	(0.041)	(0.876)
1997 Crisis		-0.012	-0.037**	0.011	-0.028	0.037	-0.194	-0.033	0.013	-0.289
(0.015)	(0.018)	(0.022)		(0.037)	(0.065)	(0.250)		(0.053)	(0.076)	(0.199)
Africa		0.006	0.041	0.014	-0.038	0.043	-0.169	-0.022	0.081	-0.331
(0.006)	(0.041)	(0.022)		(0.025)	(0.039)	(0.195)		(0.031)	(0.062)	(0.200)
Americas		0.005	0.032	0.014	-0.056**	0.063	0.299	-0.045	0.084	0.140
(0.006)	(0.041)	(0.042)		(0.022)	(0.046)	(0.190)		(0.035)	(0.058)	(0.235)
Ceiling_External_Debt(MT<)		0.007	0.020	0.063	0.040***	0.037	-0.054	0.006	0.011	-0.453
(0.005)	(0.020)	(0.046)		(0.014)	(0.039)	(0.263)		(0.013)	(0.037)	(0.682)
Floor_Int'l_Reserves		0.010*	0.014	0.005	0.037*	0.027	0.136	0.023	0.043*	0.133
(0.005)	(0.011)	(0.024)		(0.021)	(0.021)	(0.164)		(0.016)	(0.024)	(0.146)
Ceiling_External_Arrears		-0.001	-0.003	0.006	0.033**	0.013	0.029	0.010	0.019	-0.239
(0.004)	(0.006)	(0.022)		(0.014)	(0.014)	(0.132)		(0.021)	(0.026)	(0.165)
Ceiling_Gov't_Credit		-0.010**	-0.005	-0.160***	-0.003	0.009	0.026	0.028**	0.011	0.724
(0.005)	(0.007)	(0.042)		(0.012)	(0.026)	(0.435)		(0.013)	(0.017)	(0.720)
Ceiling_Gov't_Deficit		-0.004	-0.008	0.041*	-0.058***	-0.021**	-0.302	-0.021	-0.014	-0.026
(0.004)	(0.005)	(0.022)		(0.018)	(0.011)	(0.203)		(0.021)	(0.024)	(0.156)
Ceiling_External_Debt(ST)		-0.001	-0.002	-0.085**	-0.020*	-0.009	0.109	0.006	0.014	-0.066
(0.004)	(0.005)	(0.040)		(0.012)	(0.013)	(0.237)		(0.010)	(0.014)	(0.242)
Ceiling_CB_Net_Dom_Assets		0.002	-0.009	0.089***	0.010	-0.013	-0.012	0.041**	-0.006	0.524*
(0.006)	(0.007)	(0.032)		(0.020)	(0.016)	(0.413)		(0.017)	(0.019)	(0.292)
Civil_Service_Wage/Empl.		0.003	0.010	0.009	-0.002	-0.002	0.719*	-0.008	-0.009	0.989
(0.004)	(0.007)	(0.080)		(0.009)	(0.013)	(0.380)		(0.009)	(0.014)	(0.721)
Improve_Econ_Statistics		0.008*	0.001	-0.144	-0.009	-0.002	0.001	-0.028***	-0.006	0.159
(0.005)	(0.006)	(0.090)		(0.010)	(0.011)	(0.731)		(0.010)	(0.012)	(1.016)
Open_Current&Capital_Account		-0.002	0.006	0.002	-0.043**	-0.036**	-0.493*	-0.012	-0.019	-0.230
(0.005)	(0.006)	(0.021)		(0.021)	(0.015)	(0.261)		(0.018)	(0.023)	(0.158)
Financial_Sector_Reform		0.002	0.013*	0.031	0.003	0.018	-0.240	-0.001	0.004	-0.244
(0.005)	(0.007)	(0.025)		(0.015)	(0.015)	(0.209)		(0.018)	(0.022)	(0.256)
Reduce_Trade_Tariff/Quota		0.001	0.006	-0.025	0.023	-0.005	0.402	-0.029*	-0.051*	0.039
(0.004)	(0.005)	(0.024)		(0.024)	(0.014)	(0.257)		(0.017)	(0.026)	(0.126)
Gov't_Enterprise_Pricing		-0.002	0.005	-0.062*	0.017	0.001	0.190	0.033*	-0.004	0.130
(0.004)	(0.007)	(0.032)		(0.011)	(0.013)	(0.214)		(0.018)	(0.013)	(0.264)
CB_Stats_Regs_Indep.		-0.002	0.001	-0.126***	-0.010	-0.013	-0.074	-0.007	-0.022	-0.244
(0.004)	(0.008)	(0.038)		(0.011)	(0.016)	(0.250)		(0.013)	(0.021)	(0.335)
Labor_Mkt_Wage/Empl.		0.009	-0.031*	-	-0.025	-0.003	-	-0.025	-0.009	-
(0.007)	(0.018)			(0.016)	(0.030)			(0.019)	(0.049)	
BOP_Stabilization ¹		-0.005	-0.012	-0.015	0.042**	0.087*	0.398**	0.053***	0.179	0.167
(0.005)	(0.013)	(0.025)		(0.018)	(0.044)	(0.163)		(0.020)	(0.118)	(0.132)
BOP_Shocks_Precautionary ²		0.009	0.009	-	0.012	0.020	-	-0.006	0.048	-
(0.006)	(0.018)			(0.019)	(0.032)			(0.021)	(0.052)	
Struct_Adj_Poverty_Growth ³		0.004	0.002	-	-0.023*	-0.007	-	0.009	0.048*	-
(0.005)	(0.011)			(0.014)	(0.018)			(0.017)	(0.025)	
Non_Financial_Reforms ⁴		0.001	-0.004	-0.038	0.008	0.006	0.432**	0.011	0.041***	0.211
(0.005)	(0.007)	(0.033)		(0.016)	(0.018)	(0.200)		(0.012)	(0.015)	(0.177)
Elections		-0.001	-0.110*	0.013	0.012	-0.019	0.149	-0.007	-0.020	0.012
(0.004)	(0.005)	(0.015)		(0.018)	(0.013)	(0.174)		(0.012)	(0.018)	(0.116)
Conflicts		-0.005	-0.007	-0.038**	0.000	-0.019	0.005	-0.003	-0.007	-0.033
(0.005)	(0.006)	(0.016)		(0.012)	(0.012)	(0.120)		(0.013)	(0.019)	(0.149)
Observations		597	276	71	596	276	71	595	275	69
Adjusted_R-squared		0.406	0.199	0.521	0.842	0.643	0.823	0.819	0.231	0.859
SJS_F-test ($\alpha=\delta=0$ & $\beta=1$)		1.368*	2.044***	13.64***	3.263***	1.433**	5.618***	1.573**	1.369*	13.84***
p-value ($\alpha=\delta=0$ & $\beta=1$)		0.081	0.001	0.000	0.000	0.063	0.000	0.021	0.091	0.000

Note:

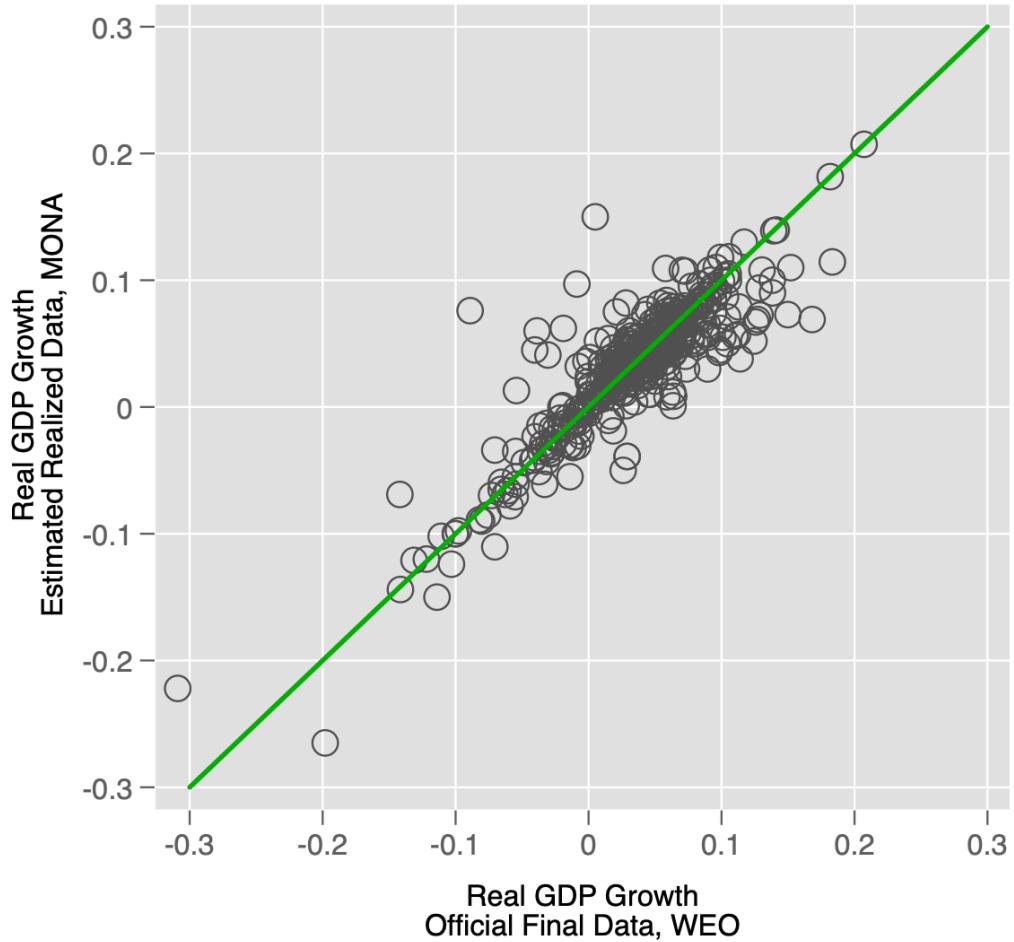
(1) Robust standard errors in parentheses unless otherwise indicated; *** p<0.01, ** p<0.05, * p<0.1

(2) ¹ SBA; ² ESF, SCF, FCL,PCL, PLL; ³ SAF, ESAF, PRGT; ⁴ PSI, PCI. See Table 1 for detailed description of programs.

(3) Insignificant variables that were included in the regressions are not included in the table to economize on space. These variables include Regions (Asia), Quantitative conditionality: Ceiling_Domestic_Arrears, Ceiling_New_Arrears/Default; Structural conditionality: Gen_Gov't.Reform, Legal/Market_Reforms, Pension_Reform, NaturalDisasters, LoanAmount.

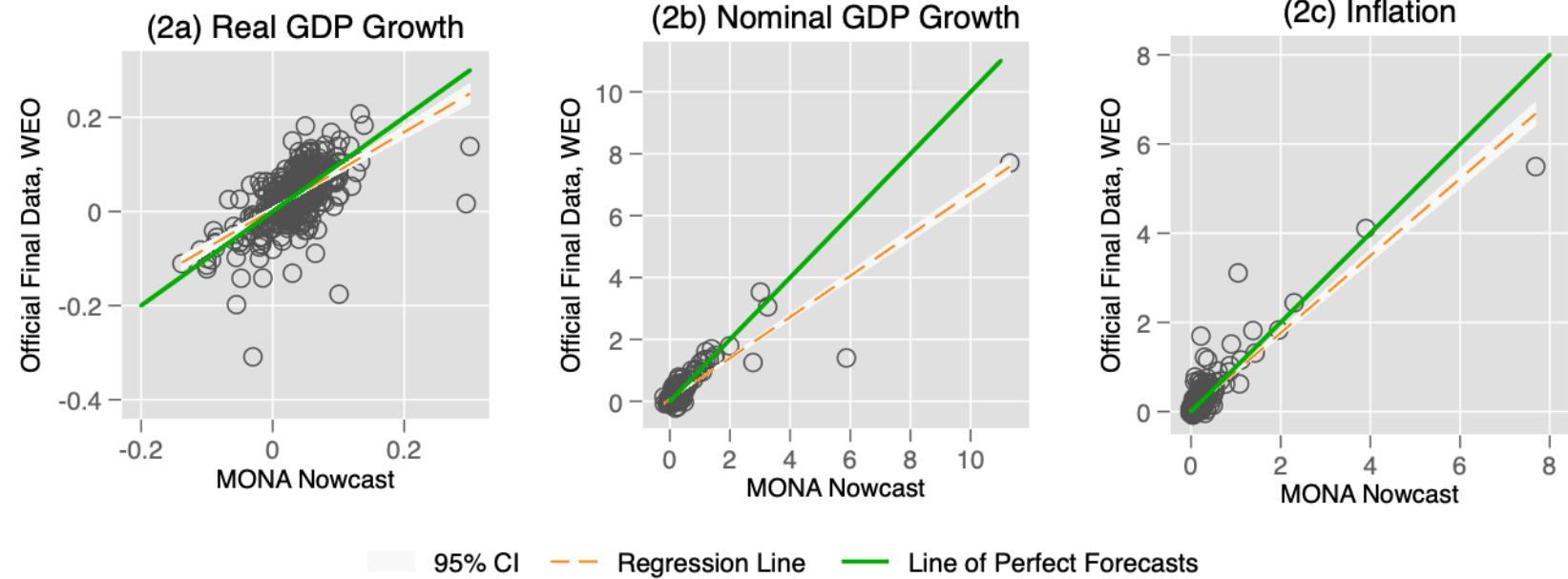
(4) Omitted dummy variables to avoid singularity: Regions (Europe) and Program Objectives ("Long-Term BOP and Structural Reforms" consisting of: ECF and EFF)

Figure 1: Official Final Data (WEO) vs. Estimates of Final Data (MONA)
(Real GDP Growth)



Source: Authors' calculations.

Figure 2: Prediction-Realization Diagrams
(Full Sample)



Source: Authors' calculations.

Figure 3: Prediction-Realization Diagrams for Subsamples

Figure 3.1: Non-Hyperinflation & Non Low-Income Countries

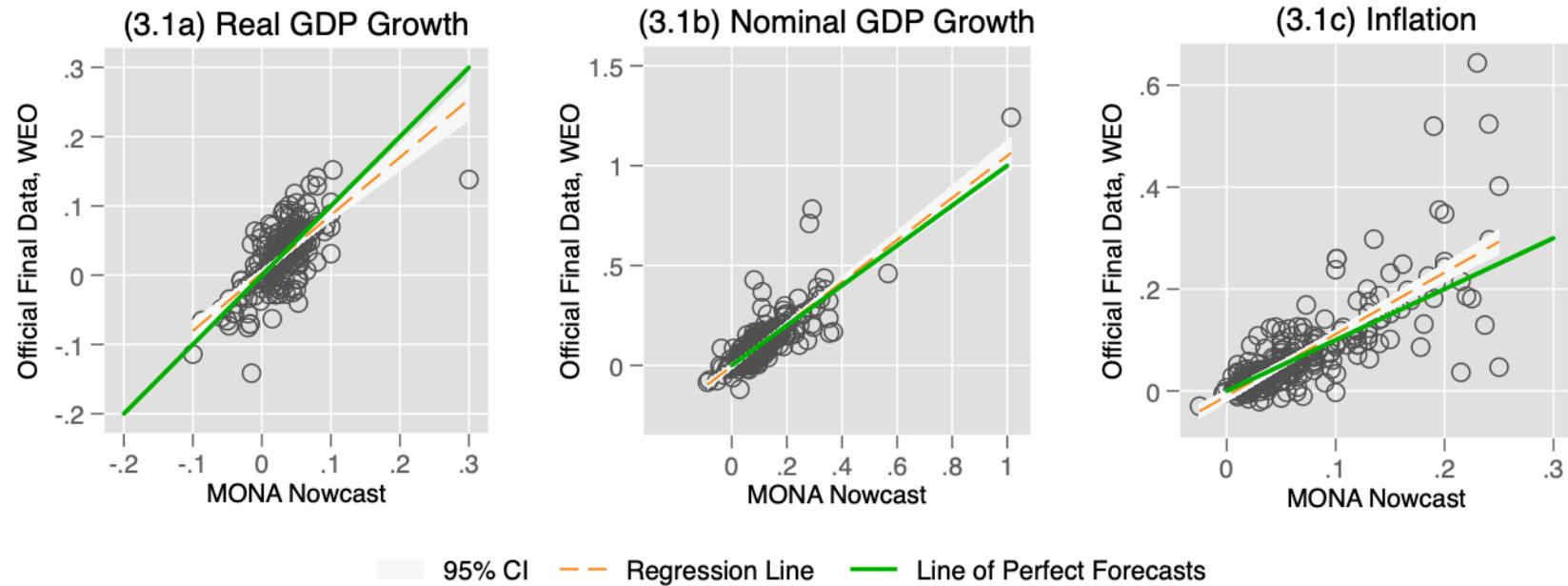


Figure 3.2: Non-Hyperinflation & Low-Income Countries

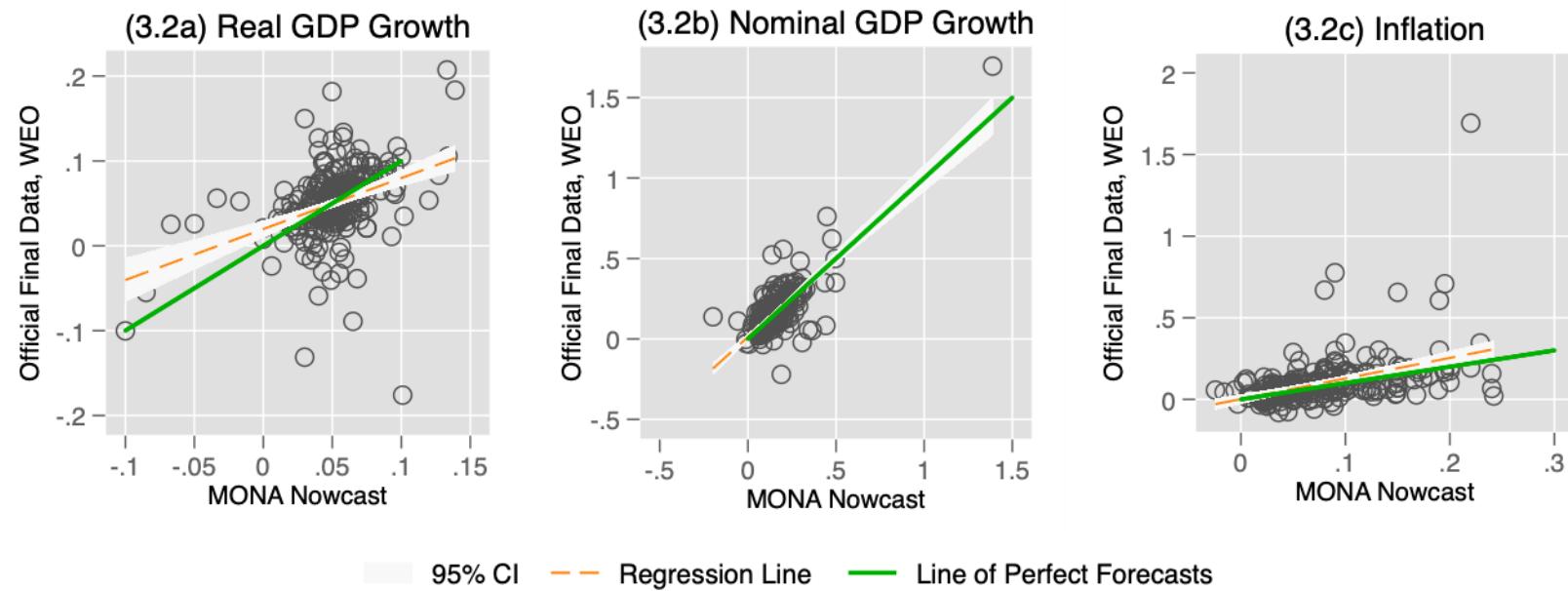
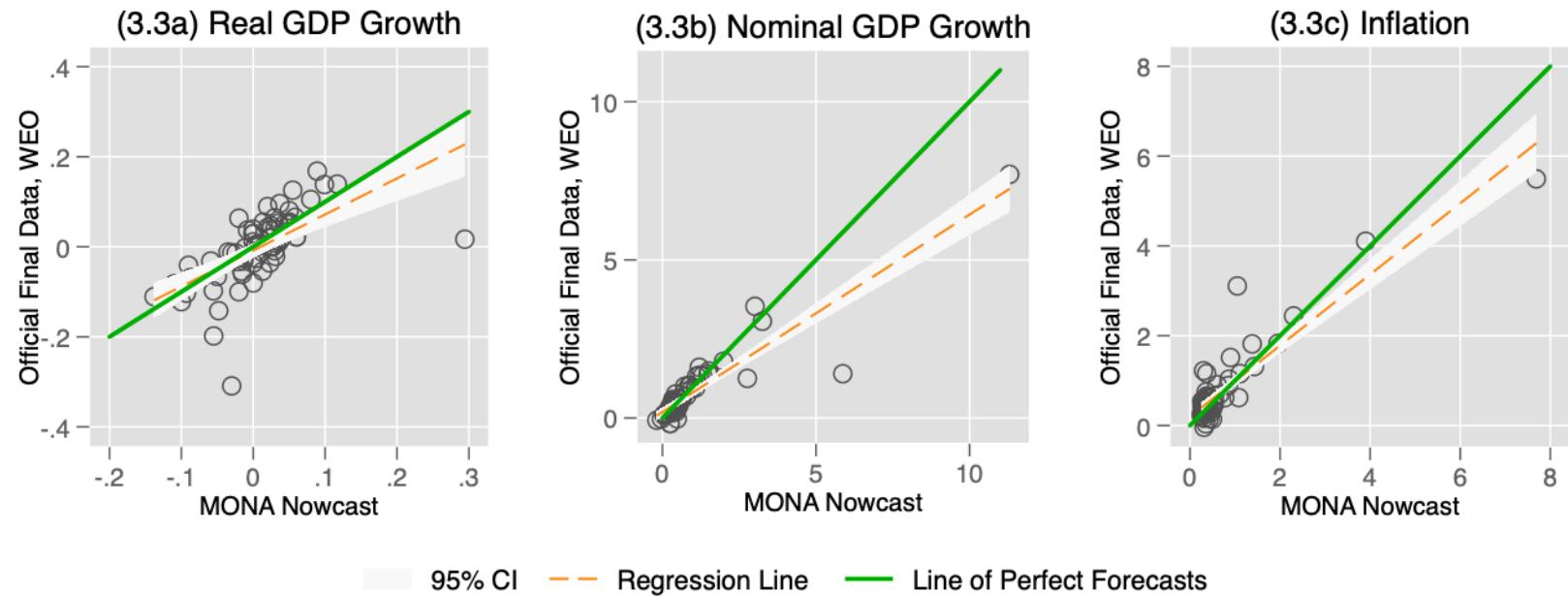


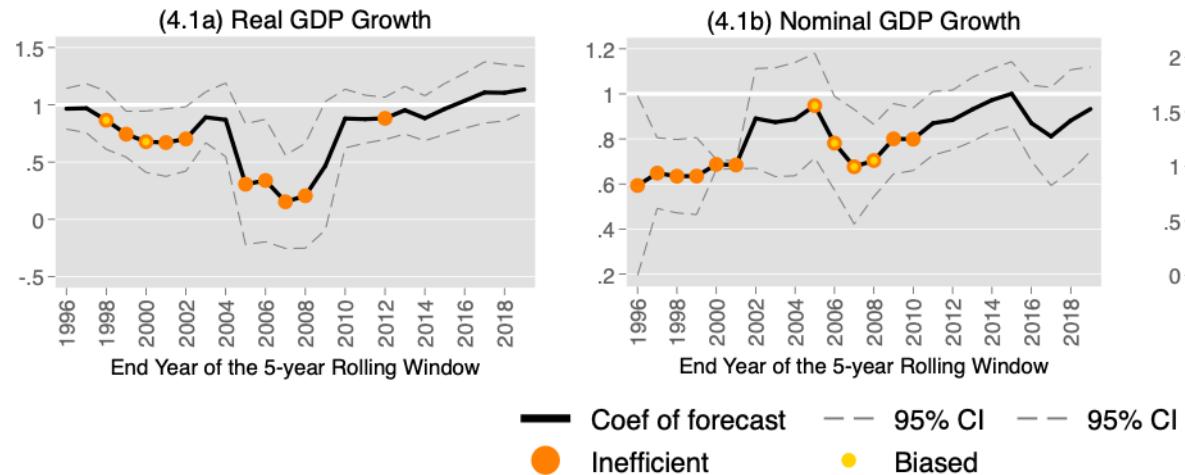
Figure 3.3: Hyperinflation Countries



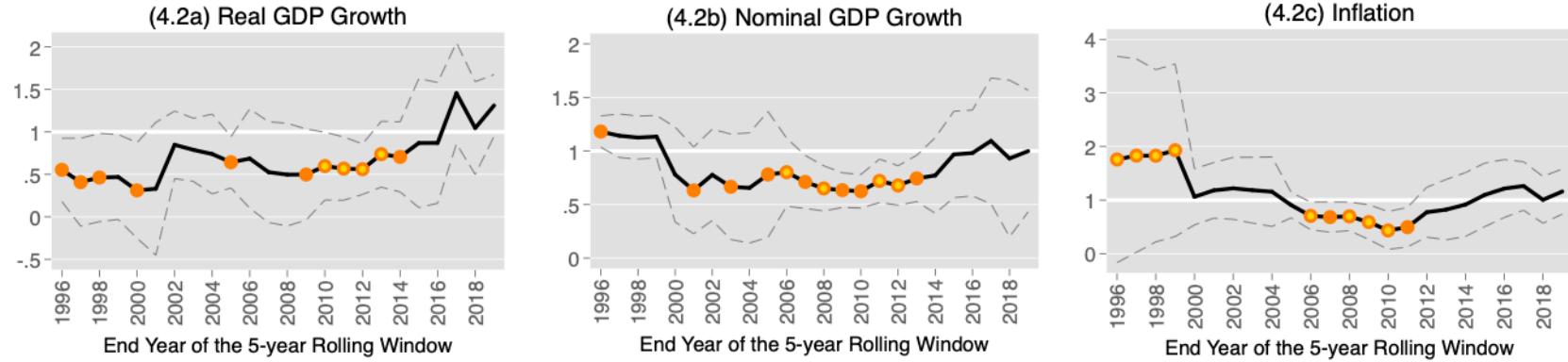
Source: Authors' calculations.

Figure 4: Nowcast Bias and Efficiency Over Time

4.1: Full sample

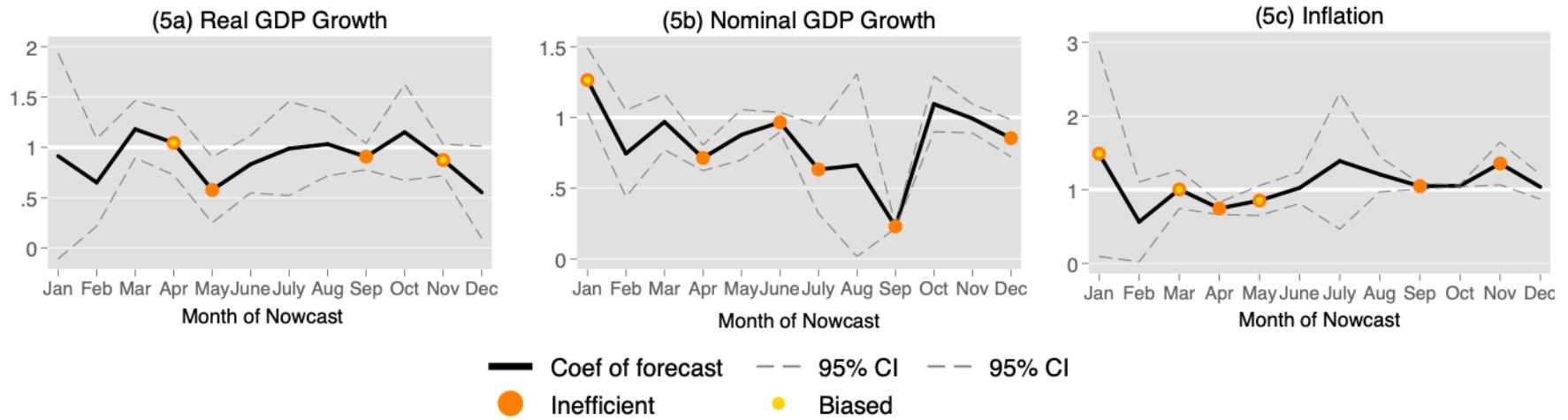


4.2: Subsample of Non-Hyperinflation LICs



Source: Authors' calculations.

Figure 5: Nowcast Horizons and Nowcast Accuracy
 (Full Sample)



Source: Authors' calculations.

Appendix A

Appendix A addresses three dimensions of the MONA database: Section A1 (“MONA Audit”) covers results of our MONA audit including a list of (corrected) errors. Section A2 (“MONA Harmonization”) describes the construction of the time series of IMF program nowcasts from 1992 to 2019. Section A3 (“Our Dataset”) details our dataset.

A1. MONA Audit

The MONA database presents challenges to researchers as it contains a wide range of errors. To complicate matters, the database does not identify release dates, so updates/corrections to the database cannot be identified by vintages. Results of our audit are based on the MONA version downloaded November 19, 2020, which is archived at tinyurl.com/monamirror. We audited MONA and corrected the following 11 different types of errors:

Data Entry Errors

- (1) Temporal Errors (the right data entered for the wrong program year)
- (2) Zeros Identify Missing Values
- (3) Data Entered with Wrong Signs
- (4) Typos and Spelling Mistakes
- (5) Wrong Line Items Entered

Inconsistencies

- (6) Currency Unit Magnitude Inconsistencies
- (7) Indicator Variable Inconsistencies
- (8) Rates vs Level Inconsistencies
- (9) Base Year Inconsistencies

Corrected Data from IMF Archives (Executive Board Documents)

- (10) Missing Data Corrected
- (11) Outliers Verified and Corrected

Important Note: Errors cited in this paper that are corrected in future work or in the MONA database must cite this paper as the source.

A.1.1 Temporal Errors

MONA identifies “t” as the program year and reports data from t-3 to t+4. If the program year was, for example, the year 2000 for country x, the database reports 1997 to 2004 data for that program. At times, data entry confused the program year to create temporal errors by entering data t data (supposedly 2000 data) as t-1 data (1999 data). This error occurs in several forms: either (i) for an entire program, (ii) for all variables but only some reviews of a particular program, or (iii) for only some variables in only some reviews of a particular program. Table A.1.1 lists 10 programs that suffer from this error. Each program features multiple incidences of the error.

A.1.2 Zeros Identify Missing Values

MONA does not possess a consistent indicator for missing values. At times missing entries are identified as “0,” “.”, “ ”, “NA”, or “NULL.” Using zeros as missing values creates problems when some variables (e.g., debt or inflation) take zero as actual values. For inflation, we replaced exact zeros as missing data or corrected the entry if we observed four or more consecutive years of exact zero inflation, after auditing

every zero for t and t-1. Table A.1.2 lists 29 missing values which related to GDP and inflation that were erroneously entered as zeros in MONA. We identified an additional 10935 instances where exact zeros are missing values (e.g., for national accounts, exchange rates, or investment data) but we do not include that list in our Table, which pertains only to variables used in our paper.

A.1.3 Data Entered with Wrong Sign

Our audit of the MONA database produced 593 instances of variables entered with the wrong (negative) sign. This is a common issue for trade data in MONA (although the database instructions/definitions indicate otherwise). Such sign errors are prevalent and affect a wide range of variables including consumption and investment data. Errors are also not necessarily consistent within any given program, which may express a variable at times with or without a negative sign. We do not list these items in a Table since they do not affect the variables in our paper.

A.1.4 Typos and Spelling Mistakes

Table A.1.4 lists 49 instances of typos, where either (i) the entire number is wrong, (ii) one decimal is wrong, (iii) one additional integer is added, (iv) one integer is missing, (v) the wrong country is identified as the program country, (vi) the wrong year is identified as the program year, or (vii) a variable is misspelled.

A.1.5 Wrong Line Item Entered

When data entry fell into the wrong line in the loan document, data for variable x (the line item above or below) is, at times, accidentally entered for variable y. Table A.1.5 lists 2 the instances relevant to our paper.

A.1.6 Currency Unit Magnitude Inconsistencies

Table A.1.6 lists 19 instances where unit magnitudes for a given variable are inconsistent across reviews in a given program.

A.1.7 Unit Indicator Variable Inconsistency

There are 293 instances for real/nominal GDP and inflation where the indicated (i) currency magnitude, (ii) currency (USD vs. SDR), or (iii) indicator currency unit (index vs rate) is incorrect. In addition, there are 5301 of such instances for variables that do not pertain to this paper. Since our paper is in growth rates, we do not report these instances.

A.1.8 Rates vs. Levels Inconsistencies

Table A.1.8 lists 28 instances for GDP/inflation where MONA indicates growth rates (e.g. GDP growth) but the data entered is in levels, or when a variable is supposed to be the inflation rate, but the data entered is an index.

A.1.9 Unit Inconsistency: Base Years

Table A.1.9 lists 23 instances when a variable in the same program is expressed in different base years. Since MONA does not contain a separate variable that indicates the base year, any revaluation, currency reform, or change in base years cannot be easily discerned in the database. When changes in base years were apparent, we adjusted observations to have the same base year and converted the data to growth rates. Two programs had to be dropped since the base year and/or base year currency reform conversions were unclear.

A.1.10 Missing Data

Table A.1.10 lists the 17 missing observations in the original MONA database that we updated with GDP and Inflation data from the IMF archives (Executive Board Documents).

A.1.11 Verified / Corrected Outliers

Table A.1.11 reports 92 outliers for real/nominal GDP and inflations that we audited/verified/corrected for program year t and t-1. After all missing datapoints were audited, we audited all observations that were 3 standard deviations from the mean. After the first round of audited outliers, the distribution changed and we audited yet another round of outliers 3 standard deviations from the mean to verify that large deviations represent the actual data.

A2. MONA Harmonization

The IMF MONA database consists of two parts: Part I: 1992-2002 and Part II: 2002-today. The newer MONA files report real GDP in local currency and in levels, while the older MONA files report it in growth rates. We calculated growth rates for the newer MONA files. Newer MONA files also report “end-of-period CPI” in levels (as an index), while older MONA files report “end-of-period CPI” prices as inflation rates (in percentages). Again we calculated inflations rates from the level data for newer MONA files.

A3. Our Dataset

To construct our dataset, we used the World Economic Outlook (WEO) data as “official final data” and MONA data issued at the time the program was approved as “nowcasts.” To ensure consistency, we mapped MONA data that are levels with WEO data in levels and then calculated growth rates. There are exceptions: First, when end-of-period inflation data was missing in MONA or from Executive Board Documents in IMF archives, we used period-average inflation data; seven such instances are documented in Table A.3.1 below. When WEO official final data was missing, we used data from MONA’s last review; 29 instances are documented in Table A.3.1 below. When WEO data seemed to contain errors we also used MONA’s last review data; one instance is documented in Table A.3.1. below.

We used growth rates as the unit of analysis paper because IMF projections are based on the growth rates. Also, level data in MONA is at times report in different units or magnitudes (as described in Appendix A.1.7 and A.1.8). Focusing on growth rates resolved the inconsistency issues. Our current dataset includes 602 programs for three variables: real GDP growth, nominal GDP growth, and inflation from 1992-2019. We had to drop two programs due to unresolved issues (see Table A.1.9). The data coverage differs slightly for each variable due to variations in the availability of original data in the IMF Archives:

- Real GDP growth data covers 597 programs. We dropped 3 programs with missing final data (in both WEO and MONA).
- Nominal GDP growth data covers 596 programs. We dropped 2 programs with missing nowcasts data and 2 programs with missing final data (in both WEO and MONA).
- Inflation rate data covers 595 programs. We dropped 5 programs with missing final data (in both WEO and MONA).

Table A.1.1: MONA Temporal Errors

Count	Arrange- ment	Country Name	Prog. Year	Mneumonic	Review Type	Year (t-3 -t+4)	Correction
1	7	Estonia	1993	All	Last	All	corrected data using IMF archives (moved data one year forward)
2	15	El Salvador	1993	All	Last	All	corrected data using IMF archives (moved data one year forward)
3	132	Sierra Leone	1995	NI_Y, RGDPC	R0	All	corrected data using IMF archives (moved data one year forward)
4	256	Indonesia	1998	NI_Y, PCPIC, RGDPC	All	All	corrected data using IMF archives (moved data one year backward)
5	275	Indonesia	1999	ENDA, NGDP, PCPIC, RGDPC	All	All	corrected data using IMF archives (moved data one year backward)
6	552	Dominican Rep.	2005	All	All	All	corrected data using IMF archives (moved data two years backward)
7	571	Madagascar	2006	All	Last	All	corrected data using IMF archives (moved data one year forward)
8	579	Gabon	2007	All	R1–Last	All	corrected data using IMF archives (moved data one year forward)
9	687	Tanzania	2012	BFOL_O	Last	All	corrected data using IMF archives (moved data two years backward)
10	695	Solomon Islands	2012	FMB, FBA, FCG, FDS, FGS, FFS	R1–Last	All	corrected data using IMF archives (moved data one year forward)

Table A.1.2: Zeros Identify Missing Values

Count	Arrange- ment	Country Name	Prog . .	Mnemonic	Review Type	Year (t-3 -t+4)	Correction
1	127	Georgia	1995	NGDP	R0	t-3	data corrected using IMF archives
2	250	Mauritania	1997	PCPIC	R0	t-1	data corrected using IMF archives
3	264	Central African Republic	1998	PCPIC	R0	t-1	Zero verified by EBS document
4	281	Argentina	1998	PCPIC	R0	t-2 to t-1	Zero verified by EBS document
5	337	Indonesia	2000	PCPIC	R0	t-1	Zero verified by EBS document
6	507	Albania	2002	NGDP	R6	All	Replaced zeros with missing values
7	507	Albania	2002	NGDP_R	R6	All	Replaced zeros with missing values
8	507	Albania	2002	PCPIE	R6	All	Replaced zeros with missing values
9	526	Nepal	2003	NGDP	R2-R3	t-3 to t-2	Replaced zeros with missing values
10	526	Nepal	2003	NGDP_R	R2-R3	t-3 to t-2	Replaced zeros with missing values
11	544	Mozambique	2004	NGDP	R1-R2	t+4	Replaced zeros with missing values
12	544	Mozambique	2004	NGDP_R	R1-R2	t+4	Replaced zeros with missing values
13	551	Niger	2005	NGDP_R	R5	t-3	Replaced zeros with missing values
14	560	Benin	2005	PCPIE	R0	t-1 to t+4	data corrected using IMF archives
15	590	Liberia	2008	PCPIE	R7	All	Replaced zeros with missing values
16	656	Senegal	2010	PCPIE	R6-R7	All	Replaced zeros with missing values
17	662	Romania	2011	NGDP_R	R7-R8	t+4	Replaced zeros with missing values
18	678	Burundi	2012	NGDP	R0	t+3 to t+4	Replaced zeros with missing values
19	678	Burundi	2012	NGDP_R	R0	t+3 to t+4	Replaced zeros with missing values
20	681	Niger	2012	PCPIE	R2-R7	All	Replaced zeros with missing values
21	685	Gambia, The	2012	PCPIE	R0	All	data corrected using IMF archives
22	708	Burkina Faso	2013	NGDP	R0	t+4	Replaced zeros with missing values
23	708	Burkina Faso	2013	NGDP_R	R0	t+4	Replaced zeros with missing values
24	709	Albania	2014	PCPIE	R2-R3	All	data corrected using IMF archives
25	714	Tanzania	2014	PCPIE	R0	All	data corrected using IMF archives
26	729	Senegal	2015	PCPIE	R3	All	Replaced zeros with missing values
27	731	Sao Tome and Principe	2015	PCPIE	R0	All	data corrected using IMF archives
28	739	Rwanda	2016	PCPIE	R0	t to t+4	data corrected using IMF archives
29	741	Iraq	2016	PCPIE	R0	All	data corrected using IMF archives

Table A.1.4: Typos and Spelling Mistakes

Count	Arrangement	Country Name	Prog. Year	Mneumonic	Review Type	Year (t-3 -t+4)	Correction
1	15	El Salvador	1993	programyear	R2	All	programyear corrected
2	18	Latvia	1993	programyear	R1–Last	All	programyear corrected
3	75	Turkey	1994	PCPIC	R0	All	data corrected using IMF archives
4	84	Algeria	1995	DL	Last	All	data corrected using IMF archives
5	117	Albania	1994	countryname	All	All	wrong countryname corrected
6	117	Albania	1994	countrycode	All	All	wrong countryname corrected
7	127	Georgia	1995	NGDP	R0	t	data corrected using IMF archives
8	132	Sierra Leone	1995	programyear	R0	All	programyear corrected
9	136	Haiti	1995	PCPIC	R0	t	data corrected using IMF archives
10	143	Pakistan	1996	programyear	R0–R1	All	programyear corrected
11	156	Guyana	1996	BK_SP	Last	All	data corrected using IMF archives
12	160	Russian Federation	1995	PCPIC	R0	All	data corrected using IMF archives
13	205	Vietnam	1996	boarddocno	R1	All	board document typo corrected
14	206	Congo, Rep.	1996	GCECY	R0	All	data corrected using IMF archives
15	207	Ethiopia	1997	reviewtype	All	All	reviewtype lables corrected
16	212	Kyrgyz Republic	1997	ENDA	Last	All	data corrected using IMF archives
17	230	Burkina Faso	1996	programyear	R0	All	data corrected using IMF archives
18	242	Bosnia Herzegovin	1998	RGDPC	R0	t-3	data corrected using IMF archives
19	250	Mauritania	1997	PCPIC	R0	t-3 to t-1	data corrected using IMF archives
20	274	Ukraine	1998	NGDP	Last	All	data corrected using IMF archives
21	274	Ukraine	1998	PCPIC	R0	All	data corrected using IMF archives
22	274	Ukraine	1998	programyear	R5–R6	All	programyear corrected
23	295	Yemen	1998	NGDP	R0	t	data corrected using IMF archives
24	402	Moldova	2000	BXS_O	R0	All	data corrected using IMF archives
25	506	Bosnia Herzegovin	2002	NGDP	R0	All	data corrected using IMF archives
26	510	Argentina	2003	NGDP	R0	All	data corrected using IMF archives
27	510	Argentina	2003	NGDP_R	R0	All	data corrected using IMF archives
28	510	Argentina	2003	PCPIE	R0	All	data corrected using IMF archives
29	521	Ghana	2003	PCPIE	R0	All	data corrected using IMF archives
30	527	Nicaragua	2002	programyear	R10	All	programyear corrected
31	535	Uruguay	2002	NGDP_R	R0	All	data corrected using IMF archives
32	535	Uruguay	2002	PCPIE	R0	All	data corrected using IMF archives
33	539	Dominican Rep.	2003	NGDP	R0	All	data corrected using IMF archives
34	539	Dominican Rep.	2003	NGDP_R	R0	All	data corrected using IMF archives
35	539	Dominican Rep.	2003	PCPIE	R0	All	data corrected using IMF archives
36	545	Peru	2004	PCPIE	R0	All	data corrected using IMF archives
37	560	Benin	2005	PCPIE	R0	All	data corrected using IMF archives
38	560	Benin	2005	boarddocno	R0	All	board document typo corrected
39	564	Iraq	2005	NI	R0	All	data corrected using IMF archives
40	572	Haiti	2006	GCENL	Last	All	data corrected using IMF archives
41	598	Djibouti	2008	NGDP_R	R0	All	data corrected using IMF archives
42	607	Congo, Rep.	2008	NGDP	R0	All	data corrected using IMF archives
43	628	Kyrgyz Rep.	2008	reviewtype	All	All	reviewtype lables corrected
44	681	Niger	2012	programyear	R8	All	programyear corrected
45	707	Mali	2013	NCG	R0	All	data corrected using IMF archives
46	724	Ukraine	2015	reviewtype	All	All	reviewtype lables corrected
47	734	Kenya	2016	reviewtype	All	All	reviewtype lables corrected
48	764	Mauritania	2017	programyear	R0–R4	All	programyear corrected
49	All	All	All	intialenddate	All	All	spelling error corrected

Table A.1.5: Wrong Line Item Entered

Count	Arrange- ment	Country Name	Prog. Year	Mneumonic	Review Type	Year (t-3 -t+4)	Correction
1	560	Benin	2005	PCPIE	R0	All	data corrected using IMF archives
2	610	Sao Tome and Principe	2009	NGDP_R	All	All	data corrected using IMF archives

Table A.1.6: Wrong Currency Unit Entered

Count	Arrange- ment	Country Name	Prog. Year	Mneumonic	Review Type	Year (t-3 -t+4)	Correction
1	23	Pakistan	1993	indicatorcurrency of NGDP	All	All	Changed to "NCU (billions)"
2	70	Poland	1994	ENDA	R0	All	Divided value by 10000
3	70	Poland	1994	FMB	R2	All	Divided value by 1000
4	70	Poland	1994	FNDA	R3	All	Divided value by 1000
5	70	Poland	1994	NGDP	R1	All	Divided value by 1000
6	75	Turkey	1994	ENDA	Last	All	Divided value by 1000
7	84	Algeria	1995	ENDA	R0	All	Divided value by 1000
8	164	Russian Federation	1996	ENDA	R0	All	Divided value by 1000
9	164	Russian Federation	1996	FMB	R6	All	Divided value by 1000
10	164	Russian Federation	1996	FNDA	R7	All	Divided value by 1000
11	164	Russian Federation	1996	NGDP	R5	All	Divided value by 1000
12	199	Croatia	1997	ENDA	Last	All	Divided value by 1000
13	317	Turkey	1999	NGDP	R0	All	Divided value by 1000
14	398	Bulgaria	2002	ENDA	R0	All	Divided value by 1000
15	398	Bulgaria	2002	NGDP	R4	All	Divided value by 1000
16	517	Croatia	2003	indicatorcurrency of NGDP	R0-R1	All	Changed to "NCU (billions)"
17	517	Croatia	2003	indicatorcurrency of PCPIE	R0-R1	All	Changed to "Index Number"
18	566	Grenada	2006	NGDP_R	Last	All	Multipled value by 10
19	580	Mozambique	2007	PCPIE	R0	All	Divided value by 1000

Table A.1.8: Rates vs. Levels Inconsistencies

Count	Arrange- ment	Country Name	Prog. Year	Mnemonic	Review Type	Year (t-3 -t+4)	Correction
1	119	Argentina	1992	NGDP	R5–R6	All	corrected to rates
2	510	Argentina	2003	NGDP_R	R0	All	corrected to rates
3	510	Argentina	2003	PCPIE	R0	All	corrected to rates
4	521	Ghana	2003	PCPIE	R0	All	corrected to rates
5	527	Nicaragua	2002	PCPIE	R0	All	corrected to rates
6	535	Uruguay	2002	NGDP_R	R0	All	corrected to rates
7	535	Uruguay	2002	PCPIE	R0	All	corrected to rates
8	539	Dominican Republic	2003	NGDP_R	R0	All	corrected to rates
9	539	Dominican Republic	2003	PCPIE	R0	All	corrected to rates
10	545	Peru	2004	PCPIE	R0	All	corrected to rates
11	556	Turkey	2005	PCPIE	All	All	corrected to rates
12	560	Benin	2005	PCPIE	R0	All	corrected to rates
13	562	North Macedonia, Rep.	2005	PCPIE	R0-R1	All	corrected to rates
14	564	Iraq	2005	PCPIE	R0	All	corrected to rates
15	566	Grenada	2006	PCPIE	R0	All	corrected to rates
16	572	Haiti	2006	PCPIE	R0	All	corrected to rates
17	580	Mozambique	2007	PCPIE	R0	All	corrected to rates
18	588	Iraq	2007	PCPIE	R0	All	corrected to rates
19	591	Honduras	2008	PCPIE	R0	All	corrected to rates
20	598	Djibouti	2008	NGDP_R	R0	All	corrected to rates
21	610	Sao Tome and Principe	2009	NGDP_R	All	All	corrected to rates
22	685	Gambia, The	2012	PCPIE	R0	All	corrected to rates
23	709	Albania	2014	PCPIE	R0	All	corrected to rates
24	714	Tanzania	2014	PCPIE	R0	All	corrected to rates
25	718	Yemen	2014	PCPIE	R0	All	corrected to rates
26	731	Sao Tome and Principe	2015	PCPIE	R0	All	corrected to rates
27	739	Rwanda	2016	PCPIE	R0	All	corrected to rates
28	741	Iraq	2016	PCPIE	R0	All	corrected to rates

Table A.1.9: Unit Inconsistency: Base Years

Count	Arrange- ment	Country Name	Prog. Year	Mneumonic	Review Type	Year (t-3 -t+4)	Correction
1	16	Kyrgyz Republic	1993	All	All	All	Unresolved. dropped
2	108	Kazakhstan	1994	All	All	All	Unresolved. dropped
3	532	Sierra Leone	2001	PCPIE	Last	All	Converted to rates
4	533	Tanzania	2000	PCPIE	Last	All	Converted to rates
5	538	Burundi	2004	PCPIE	Last	All	Converted to rates
6	547	Zambia	2004	PCPIE	Last	All	Converted to rates
7	549	Bulgaria	2004	PCPIE	Last	All	Converted to rates
8	554	Kyrgyz Republic	2005	PCPIE	Last	All	Converted to rates
9	561	Sao Tome and Principe	2005	PCPIE	Last	All	Converted to rates
10	565	Albania	2006	PCPIE	Last	All	Converted to rates
11	567	Moldova	2006	PCPIE	Last	All	Converted to rates
12	568	Paraguay	2006	PCPIE	Last	All	Converted to rates
13	596	Burundi	2008	PCPIE	Last	All	Converted to rates
14	617	Romania	2009	PCPIE	Last	All	Converted to rates
15	619	Ghana	2009	PCPIE	Last	All	Converted to rates
16	620	Sri Lanka	2009	PCPIE	Last	All	Converted to rates
17	623	Angola	2010	PCPIE	Last	All	Converted to rates
18	625	Congo, Democ. Rep.	2010	PCPIE	Last	All	Converted to rates
19	635	El Salvador	2010	PCPIE	Last	All	Converted to rates
20	678	Burundi	2012	PCPIE	Last	All	Converted to rates
21	697	Jamaica	2013	PCPIE	Last	All	Converted to rates
22	704	Romania	2013	PCPIE	Last	All	Converted to rates
23	712	Seychelles	2014	PCPIE	Last	All	Converted to rates

Table A.1.10: Missing Data Filled

Count	Arrange- ment	Country Name	Prog. Year	Mnemonic	Review Type	Year (t-3 -t+4)	Correction
1	5	Czech Republic	1993	NGDP	Last	All available	entered data using IMF archives
2	95	Ukraine	1995	RGDPC	R0	All available	entered data using IMF archives
3	127	Georgia	1995	NGDP	R0	All available	entered data using IMF archives
4	203	Senegal	1997	PCPIC	R0	All available	entered data using IMF archives
5	277	Senegal	1998	PCPIC	R0	All available	entered data using IMF archives
6	327	Senegal	1999	PCPIC	R0	All available	entered data using IMF archives
7	418	Turkey	2002	NGDP	R0	All available	entered data using IMF archives
8	537	Serbia & Montenegro	2002	PCPIE	R0	All available	entered data using IMF archives
9	545	Peru	2004	PCPIE	R0	All available	entered data using IMF archives
10	624	Maldives	2009	NGDP_R	R0	All available	entered data using IMF archives
11	650	Kosovo, Rep.	2010	PCPIE	R0	All available	entered data using IMF archives
12	685	Gambia, The	2012	PCPIE	R0	All available	entered data using IMF archives
13	709	Albania	2014	PCPIE	R0	All available	entered data using IMF archives
14	714	Tanzania	2014	PCPIE	R0	All available	entered data using IMF archives
15	731	Sao Tome and Principe	2015	PCPIE	R0	All available	entered data using IMF archives
16	739	Rwanda	2016	PCPIE	R0	All available	entered data using IMF archives
17	741	Iraq	2016	PCPIE	R0	All available	entered data using IMF archives

Table A.1.11: Verified / Corrected Outliers Part I

Count	Arrange- ment	Country Name	Prog. Year	Mnemonic	Correction
1	10	Ethiopia	1992	RGDPC	verified using IMF archives
2	16	Kyrgyz Republic	1993	NGDP	verified using IMF archives
3	16	Kyrgyz Republic	1993	PCPIC	verified using IMF archives
4	17	Lao People'S Dem. Rep.	1993	NGDP	not available in IMF loan archives, dropped
5	17	Lao People'S Dem. Rep.	1993	PCPIC	verified using IMF archives
6	17	Lao People'S Dem. Rep.	1993	RGDPC	verified using IMF archives
7	19	Lithuania	1993	PCPIC	verified using IMF archives
8	75	Turkey	1994	PCPIC	typo fixed using IMF archives
9	80	Bulgaria	1994	PCPIC	verified using IMF archives
10	82	Moldova	1994	NGDP	verified using IMF archives
11	82	Moldova	1994	PCPIC	verified using IMF archives
12	82	Moldova	1994	RGDPC	verified using IMF archives
13	93	Cambodia	1994	NGDP	verified using IMF archives
14	93	Cambodia	1994	PCPIC	verified using IMF archives
15	93	Cambodia	1994	RGDPC	verified using IMF archives
16	108	Kazakhstan	1994	NGDP	verified using IMF archives
17	108	Kazakhstan	1994	PCPIC	verified using IMF archives
18	118	Congo, Republic Of	1994	PCPIC	WEO data typo? Used MONA last review
19	127	Georgia	1995	NGDP	typo fixed using IMF archives
20	127	Georgia	1995	PCPIC	verified using IMF archives
21	132	Sierra Leone	1995	RGDPC	temporal issue fixed using IMF archives
22	134	Belarus	1995	NGDP	verified using IMF archives
23	134	Belarus	1995	PCPIC	verified using IMF archives
24	136	Haiti	1995	NGDP	not available in IMF loan archives, dropped
25	136	Haiti	1995	PCPIC	typo fixed using IMF archives
26	136	Haiti	1995	RGDPC	verified using IMF archives
27	139	Kyrgyz Republic	1994	NGDP	verified using IMF archives
28	139	Kyrgyz Republic	1994	PCPIC	verified using IMF archives
29	139	Kyrgyz Republic	1994	RGDPC	verified using IMF archives
30	150	Togo	1996	RGDPC	verified using IMF archives
31	158	Ghana	1995	PCPIC	verified using IMF archives
32	160	Russian Federation	1995	PCPIC	typo fixed using IMF archives
33	170	Cambodia	1995	NGDP	verified using IMF archives
34	170	Cambodia	1995	PCPIC	verified using IMF archives
35	170	Cambodia	1995	RGDPC	verified using IMF archives
36	174	Guinea-Bissau	1996	PCPIC	verified using IMF archives
37	181	Bulgaria	1996	PCPIC	verified using IMF archives
38	187	Uzbekistan	1996	PCPIC	verified using IMF archives
39	202	Bulgaria	1997	NGDP	verified using IMF archives
40	202	Bulgaria	1997	PCPIC	verified using IMF archives
41	202	Bulgaria	1997	RGDPC	verified using IMF archives
42	210	Romania	1997	PCPIC	verified using IMF archives
43	222	Mexico	1995	PCPIC	verified using IMF archives
44	228	Sierra Leone	1997	PCPIC	verified using IMF archives
45	228	Sierra Leone	1997	RGDPC	verified using IMF archives
46	242	Bosnia & Herzegovina	1998	RGDPC	typo fixed using IMF archives

(Table A.1.11 continued)

Count	Arrange- ment	Country Name	Prog. Year	Mnemonic	Correction
47	256	Indonesia	1998	NGDP	verified using IMF archives
48	256	Indonesia	1998	PCPIC	temporal issue fixed using IMF archives
49	256	Indonesia	1998	RGDPC	temporal issue fixed using IMF archives
50	275	Indonesia	1999	NGDP	temporal issue fixed using IMF archives
51	275	Indonesia	1999	PCPIC	temporal issue fixed using IMF archives
52	275	Indonesia	1999	RGDPC	temporal issue fixed using IMF archives
53	295	Yemen	1998	NGDP	typo fixed using IMF archives
54	506	Bosnia & Herzegovina	2002	NGDP	typo fixed using IMF archives
55	508	Argentina	2003	PCPIE	not available in IMF loan archives, dropped
56	510	Argentina	2003	NGDP	typo fixed using IMF archives
57	510	Argentina	2003	NGDP_R	typo fixed using IMF archives
58	510	Argentina	2003	PCPIE	typo fixed using IMF archives
59	520	Gambia, The	2002	NGDP_R	verified using IMF archives
60	521	Ghana	2003	PCPIE	typo fixed using IMF archives
61	532	Sierra Leone	2001	NGDP_R	verified using IMF archives
62	535	Uruguay	2002	NGDP_R	typo fixed using IMF archives
63	535	Uruguay	2002	PCPIE	typo fixed using IMF archives
64	539	Dominican Republic	2003	NGDP	typo fixed using IMF archives
65	539	Dominican Republic	2003	NGDP_R	typo fixed using IMF archives
66	539	Dominican Republic	2003	PCPIE	typo fixed using IMF archives
67	546	Ukraine	2004	NGDP	verified using IMF archives
68	552	Dominican Republic	2005	NGDP	temporal issue fixed using IMF archives
69	552	Dominican Republic	2005	NGDP_R	temporal issue fixed using IMF archives
70	552	Dominican Republic	2005	PCPIE	temporal issue fixed using IMF archives
71	564	Iraq	2005	NGDP_R	verified using IMF archives
72	566	Grenada	2006	NGDP_R	verified using IMF archives
73	588	Iraq	2007	PCPIE	verified using IMF archives
74	598	Djibouti	2008	NGDP_R	typo fixed using IMF archives
75	601	Seychelles	2008	PCPIE	verified using IMF archives
76	607	Congo, Republic Of	2008	NGDP	typo fixed using IMF archives
77	610	Sao Tome and Principe	2009	NGDP_R	typo fixed using IMF archives
78	611	Armenia	2009	NGDP	verified using IMF archives
79	611	Armenia	2009	NGDP_R	verified using IMF archives
80	611	Armenia	2009	PCPIE	verified using IMF archives
81	625	Congo, Democratic Rep.	2010	NGDP	verified using IMF archives
82	625	Congo, Democratic Rep.	2010	NGDP_R	verified using IMF archives
83	625	Congo, Democratic Rep.	2010	PCPIE	verified using IMF archives
84	643	Sierra Leone	2010	NGDP	verified using IMF archives
85	643	Sierra Leone	2010	NGDP_R	verified using IMF archives
86	643	Sierra Leone	2010	PCPIE	verified using IMF archives
87	661	Kenya	2011	PCPIE	verified using IMF archives
88	724	Ukraine	2015	PCPIE	verified using IMF archives
89	733	Mozambique	2016	PCPIE	verified using IMF archives
90	737	Suriname	2016	PCPIE	verified using IMF archives
91	737	Suriname	2016	PCPIE	verified using IMF archives
92	770	Argentina	2018	PCPIE	verified using IMF archives

Table A.2.1: MONA Harmonization

Old MONA, 1992–2002 (Mnemonic and Description)		New MONA, 2002–today (Mnemonic and Description)		Harmonization
NGDP	Nominal GDP (in level)	NGDP	Nominal GDP (in level)	Use the level of nominal GDP to calculate the growth rates for both
RGDPC	Real GDP growth rate (in percent)	NGDP_R	Real GDP (in level)	Use the level of real GDP in the new MONA to calculate the real GDP growth, then combine with the old MONA
PCPIC	End-of-period CPI Inflation rate (in percent)	PCPIE	End-of-period CPI Index (in level)	Use the CPI index in the new MONA to calculate the annual CPI inflation, then combine with the old MONA

Table A.3.1: Construction of Our Dataset

Count	Arrange- ment	Country Name	Prog. Year	Mnemonic	Review Type	Correction
1	5	Czech Republic	1993	NGDP	Last	Used MONA "L" data, WEO data missing
2	5	Czech Republic	1993	PCPIC	Last	Used MONA "L" data, WEO data missing
3	5	Czech Republic	1993	RGDPC	Last	Used MONA "L" data, WEO data missing
4	7	Estonia	1993	NGDP	Last	Used MONA "L" data, WEO data missing
5	7	Estonia	1993	PCPIC	Last	Used MONA "L" data, WEO data missing
6	7	Estonia	1993	RGDPC	Last	Used MONA "L" data, WEO data missing
7	19	Lithuania	1993	PCPIC	Last	Used MONA "L" data, WEO data missing
8	35	Cameroon	1993	NGDP	Last	Used MONA "L" data, WEO data missing
9	75	Turkey	1994	PCPIC	R0	Used the period-average data
10	110	North Macedonia, Rep.	1995	PCPIC	Last	Used MONA "L" data, WEO data missing
11	118	Congo, Republic Of	1994	PCPIC	Last	Use MONA "L" data, WEO data 1 order of magnitude larger than any other source including World Bank
12	119	Argentina	1992	PCPIC	Last	Used MONA "L" data, WEO data missing
13	121	Lithuania	1995	PCPIC	Last	Used MONA "L" data, WEO data missing
14	121	Lithuania	1995	RGDPC	Last	Used MONA "L" data, WEO data missing
15	122	Zimbabwe	1992	PCPIC	Last	Used MONA "L" data, WEO data missing
16	122	Zimbabwe	1992	RGDPC	Last	Used MONA "L" data, WEO data missing
17	126	Argentina	1995	PCPIC	Last	Used MONA "L" data, WEO data missing
18	127	Georgia	1995	PCPIC	Last	Used MONA "L" data, WEO data missing
19	130	Zimbabwe	1992	PCPIC	Last	Used MONA "L" data, WEO data missing
20	130	Zimbabwe	1992	RGDPC	Last	Used MONA "L" data, WEO data missing
21	140	Zimbabwe	1994	PCPIC	Last	Used MONA "L" data, WEO data missing
22	140	Zimbabwe	1994	RGDPC	Last	Used MONA "L" data, WEO data missing
23	145	Argentina	1996	PCPIC	Last	Used MONA "L" data, WEO data missing
24	160	Russian Federation	1995	PCPIC	R0	Used the period-average data
25	171	Georgia	1996	PCPIC	Last	Used MONA "L" data, WEO data missing
26	203	Senegal	1997	PCPIC	R0	Used the period-average data
27	217	Venezuela	1996	NGDP	Last	Used MONA "L" data, WEO data missing
28	250	Mauritania	1997	PCPIC	R0	Used the period-average data
29	277	Senegal	1998	PCPIC	R0	Used the period-average data
30	327	Senegal	1999	PCPIC	R0	Used the period-average data
31	397	Yugoslavia	2001	NGDP	Last	Used MONA "L" data, WEO data missing
32	397	Yugoslavia	2001	PCPIC	Last	Used MONA "L" data, WEO data missing
33	397	Yugoslavia	2001	RGDPC	Last	Used MONA "L" data, WEO data missing
34	537	Serbia and Montenegro	2002	PCPIE	R0	Used the period-average data
35	537	Serbia and Montenegro	2002	NGDP	Last	Used MONA "L" data, WEO data missing
36	537	Serbia and Montenegro	2002	PCPIE	Last	Used MONA "L" data, WEO data missing
37	537	Serbia and Montenegro	2002	NGDP_R	Last	Used MONA "L" data, WEO data missing

Appendix B. Regressions for Figures 4.1, 4.2, and 5

Table B.1: Regression Output for Figure 4.1
(Nowcast Bias and Efficiency Over Time, rolling 5-year averages, full sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	
1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	
Real GDP Growth																								
Constant, α	-0.003	-0.004	-0.003	0.005	0.008	0.010	0.010	0.008*	0.008	0.034***	0.034***	0.048***	0.043***	0.020	0.003	0.001	0.001	0.000	0.006	0.000	-0.002	-0.003	-0.004	-0.005
p-value ($\alpha = 0$)	0.520	0.410	0.636	0.253	0.190	0.122	0.107	0.096	0.268	0.003	0.005	0.000	0.001	0.149	0.718	0.810	0.903	0.943	0.223	0.920	0.684	0.612	0.471	0.190
IMF Nowcast, β	0.966	0.970	0.865	0.744**	0.677**	0.670**	0.702**	0.891	0.869	0.307**	0.339**	0.154***	0.206***	0.467*	0.880	0.875	0.882	0.953	0.883	0.964	1.035	1.108	1.105	1.134
p-value ($\beta = 1$)	0.705	0.784	0.296	0.012	0.018	0.029	0.038	0.335	0.421	0.011	0.016	0.000	0.001	0.062	0.354	0.236	0.206	0.656	0.238	0.746	0.769	0.422	0.397	0.188
Observations	151	180	194	192	184	172	155	136	112	94	83	72	71	75	90	87	94	87	80	60	66	62	62	65
Adjusted R-squared	0.483	0.434	0.383	0.372	0.246	0.236	0.310	0.351	0.240	0.0644	0.0845	0.0153	0.0319	0.171	0.449	0.531	0.577	0.627	0.674	0.765	0.759	0.760	0.735	0.770
MZ F-test ($\alpha=0, \beta=1$)	0.991	1.256	3.445**	3.893**	4.034**	2.880*	2.382*	1.666	0.705	4.904***	4.401**	12.98***	6.173***	2.185	0.883	2.341	3.705**	0.236	0.809	0.0875	0.0883	0.392	0.365	0.963
p-value ($\alpha=0, \beta=1$)	0.374	0.287	0.034	0.022	0.019	0.059	0.096	0.193	0.496	0.009	0.015	0.000	0.003	0.120	0.417	0.102	0.028	0.790	0.449	0.916	0.916	0.677	0.696	0.387
HP T-test ($\gamma=0$)	-1.150	-1.520	-2.34**	-1.563	-1.840*	-1.402	-0.827	1.511	0.861	1.022	0.835	1.064	-0.270	-1.186	-0.650	-0.996	-1.212	-0.369	0.594	-0.283	-0.289	0.403	-0.091	-0.442
p-value ($\gamma=0$)	0.252	0.130	0.020	0.120	0.067	0.163	0.409	0.133	0.391	0.309	0.406	0.291	0.788	0.240	0.518	0.322	0.229	0.713	0.554	0.778	0.774	0.688	0.928	0.660
Nominal GDP Growth																								
Constant, α	0.141**	0.113***	0.104***	0.084***	0.056***	0.046***	0.018	0.021	0.026*	0.020	0.043***	0.062***	0.063***	0.027**	0.027**	0.019	0.014	0.004	0.009	-0.001	0.006	0.013	0.011	0.007
p-value ($\alpha = 0$)	0.029	0.000	0.000	0.000	0.000	0.000	0.198	0.132	0.096	0.128	0.001	0.000	0.000	0.041	0.038	0.117	0.213	0.724	0.409	0.845	0.458	0.148	0.221	0.336
IMF Nowcast, β	0.593**	0.648***	0.635***	0.635***	0.687***	0.684***	0.891	0.874	0.888	0.948	0.781**	0.677**	0.704***	0.801**	0.799***	0.869*	0.884*	0.931***	0.972***	1.001***	0.870***	0.811*	0.882***	0.933***
p-value ($\beta = 1$)	0.046	0.000	0.000	0.000	0.000	0.000	0.332	0.305	0.379	0.657	0.039	0.013	0.000	0.013	0.005	0.070	0.085	0.335	0.695	0.994	0.128	0.088	0.298	0.475
Observations	149	178	193	190	183	172	155	135	112	94	83	72	71	76	91	88	95	88	80	60	66	62	62	65
Adjusted R-squared	0.621	0.846	0.841	0.851	0.962	0.972	0.624	0.653	0.652	0.757	0.603	0.495	0.554	0.618	0.584	0.618	0.643	0.641	0.638	0.746	0.718	0.612	0.665	0.759
MZ F-test ($\alpha=0, \beta=1$)	2.554*	14.54***	13.70***	13.02***	399.4***	771.7***	0.902	1.411	2.251	3.739**	7.593***	11.62***	12.97***	3.259**	4.352**	1.692	1.561	1.702	0.467	0.0430	1.821	1.504	0.766	0.480
p-value ($\alpha=0, \beta=1$)	0.081	0.000	0.000	0.000	0.000	0.000	0.408	0.248	0.110	0.028	0.001	0.000	0.000	0.044	0.016	0.190	0.215	0.498	0.629	0.958	0.170	0.230	0.469	0.621
HP T-test ($\gamma=0$)	-0.711	-1.113	-1.079	-1.057	-0.731	-0.946	0.335	0.550	1.532	1.874*	2.023**	2.492**	2.811***	-0.165	0.104	0.466	0.008	-0.546	0.962	-0.269	-1.536	-0.859	-0.029	0.084
p-value ($\gamma=0$)	0.478	0.267	0.282	0.292	0.466	0.346	0.738	0.583	0.128	0.064	0.046	0.015	0.006	0.870	0.917	0.643	0.994	0.586	0.339	0.789	0.129	0.393	0.977	0.933
Inflation																								
Constant, α	0.048***	0.095***	0.092***	0.070***	0.048***	0.035***	-0.004	0.001	0.003	0.015	0.031***	0.033**	0.022	0.014	0.015	0.008	-0.003	0.002	-0.002	-0.019**	-0.029***	-0.031***	-0.024***	-0.016*
p-value ($\alpha = 0$)	0.005	0.000	0.000	0.000	0.000	0.000	0.661	0.912	0.825	0.109	0.005	0.012	0.117	0.371	0.343	0.622	0.798	0.857	0.848	0.028	0.002	0.001	0.007	0.094
IMF Nowcast, β	1.066	0.836*	0.799*	0.802**	0.768***	0.732***	1.174	1.070	1.101	0.823	0.691*	0.575*	0.935	0.936	0.895	0.934	1.093	0.872	0.997	1.338**	1.562***	1.680***	1.551***	1.397*
p-value ($\beta = 1$)	0.283	0.094	0.020	0.027	0.001	0.000	0.114	0.569	0.584	0.235	0.088	0.054	0.763	0.771	0.680	0.795	0.635	0.446	0.986	0.049	0.004	0.001	0.005	0.068
Observations	151	180	193	191	183	171	153	134	111	93	82	72	71	76	90	87	94	87	79	60	66	62	62	65
Adjusted R-squared	0.769	0.815	0.769	0.789	0.811	0.927	0.642	0.700	0.640	0.560	0.438	0.347	0.597	0.570	0.507	0.531	0.655	0.517	0.582	0.761	0.779	0.801	0.803	0.766
MZ F-test ($\alpha=0, \beta=1$)	5.523***	7.571***	10.12***	7.855***	11.82***	67.04***	1.699	0.633	1.310	1.367	5.323***	3.781**	5.216***	1.420	1.743	0.363	0.258	1.275	0.125	2.535*	5.204***	6.317***	4.489**	1.732
p-value ($\alpha=0, \beta=1$)	0.005	0.001	0.000	0.001	0.000	0.000	0.186	0.532	0.274	0.260	0.007	0.028	0.008	0.248	0.181	0.696	0.773	0.285	0.883	0.088	0.008	0.003	0.015	0.185
HP T-test ($\gamma=0$)	3.109***	2.157**	2.228**	1.658*	0.701	-0.093	1.514	1.105	1.485	0.210	1.230	0.253	2.499**	1.265	1.282	0.518	0.698	-1.585	-0.453	0.339	0.769	0.817	1.304	1.220
p-value ($\gamma=0$)	0.002	0.032	0.027	0.099	0.484	0.926	0.132	0.271	0.140	0.834	0.222	0.801	0.015	0.210	0.203	0.606	0.487	0.117	0.652	0.736	0.445	0.417	0.197	0.227

Note:

(1) Robust standard errors in parentheses unless otherwise indicated; *** p<0.01, ** p<0.05, * p<0.1

(2) Mincer Zarnowitz Null: Nowcast is unbiased and efficient

(3) Holden Peel Null: Nowcast is unbiased

Table B.2: Regression Output for Figure 4.2
 (Nowcast Bias and Efficiency Over Time, rolling 5-year averages, Non-Hyperinflation LICs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to	to
	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Real GDP Growth																								
Constant, α	0.017	0.024*	0.021	0.024*	0.031**	0.032*	0.009	0.015*	0.014	0.021**	0.019	0.030*	0.031*	0.034**	0.031***	0.030***	0.030***	0.023**	0.022**	0.009	0.008	-0.027*	-0.006	-0.017**
p-value ($\alpha = 0$)	0.121	0.068	0.118	0.064	0.026	0.095	0.438	0.083	0.195	0.013	0.245	0.068	0.083	0.024	0.006	0.008	0.002	0.026	0.047	0.673	0.680	0.065	0.638	0.043
IMF Nowcast, β	0.553**	0.408**	0.463**	0.469**	0.311**	0.331*	0.848	0.789	0.739	0.643**	0.686	0.526	0.497	0.498*	0.597**	0.568**	0.561***	0.738	0.706	0.869	0.871	1.455	1.045	1.311*
p-value ($\beta = 1$)	0.020	0.026	0.043	0.038	0.017	0.093	0.450	0.261	0.271	0.021	0.283	0.113	0.100	0.065	0.048	0.024	0.005	0.178	0.155	0.725	0.710	0.126	0.864	0.089
Observations	65	81	95	105	108	104	90	72	56	43	36	35	34	38	33	36	35	32	24	25	22	19	21	
Adjusted R-squared	0.154	0.059	0.067	0.070	0.015	0.011	0.151	0.170	0.117	0.102	0.175	0.154	0.134	0.169	0.360	0.475	0.549	0.560	0.529	0.500	0.524	0.756	0.612	0.747
MZ F-test ($\alpha=0, \beta=1$)	3.603**	2.865*	2.681*	2.280	2.97*	1.449	0.307	2.120	0.879	3.565**	0.701	1.860	1.601	3.125*	5.161**	4.670**	5.821***	4.178**	2.627*	0.120	0.093	2.521	0.585	2.556
p-value ($\alpha=0, \beta=1$)	0.033	0.063	0.074	0.107	0.056	0.240	0.737	0.128	0.421	0.037	0.503	0.172	0.217	0.058	0.011	0.017	0.007	0.024	0.089	0.887	0.912	0.106	0.568	0.104
HP T-test ($\gamma=0$)	-0.981	-1.229	-1.368	-0.732	-1.100	-0.590	0.301	1.330	0.338	0.707	0.325	0.664	0.309	0.996	2.11**	2.185**	2.241**	2.14**	1.391	0.239	0.094	-0.334	-0.973	-0.507
p-value ($\gamma=0$)	0.330	0.223	0.175	0.466	0.274	0.557	0.764	0.188	0.737	0.484	0.747	0.511	0.759	0.326	0.042	0.036	0.032	0.040	0.174	0.813	0.926	0.742	0.343	0.618
Nominal GDP Growth																								
Constant, α	-0.022	-0.016	-0.008	-0.006	0.039	0.055**	0.041	0.053*	0.058*	0.045	0.050**	0.059***	0.077***	0.076***	0.070***	0.061***	0.068***	0.042**	0.039	0.011	-0.001	-0.021	0.003	-0.003
p-value ($\alpha = 0$)	0.115	0.318	0.622	0.661	0.182	0.031	0.123	0.064	0.062	0.159	0.028	0.005	0.000	0.000	0.003	0.000	0.038	0.152	0.687	0.982	0.430	0.940	0.922	
IMF Nowcast, β	1.181**	1.142	1.125	1.134	0.780	0.632*	0.777	0.666	0.655	0.781	0.802	0.711**	0.651***	0.635***	0.624***	0.721***	0.678***	0.744**	0.772	0.968	0.981	1.094	0.930	0.999
p-value ($\beta = 1$)	0.016	0.167	0.219	0.183	0.327	0.074	0.302	0.180	0.184	0.456	0.215	0.023	0.002	0.000	0.000	0.009	0.001	0.021	0.196	0.870	0.923	0.742	0.843	0.998
Observations	65	81	96	105	108	104	90	71	56	43	36	35	34	38	33	36	35	32	24	25	22	19	21	
Adjusted R-squared	0.793	0.764	0.732	0.742	0.330	0.260	0.337	0.273	0.262	0.417	0.532	0.501	0.499	0.562	0.623	0.656	0.646	0.656	0.534	0.491	0.543	0.560	0.409	0.548
MZ F-test ($\alpha=0, \beta=1$)	3.109*	0.986	1.107	1.496	1.388	2.740*	1.926	2.576*	2.398*	5.048**	3.829**	4.733**	8.044***	10.72***	11.860***	5.444***	8.178***	2.931*	1.099	0.250	0.0730	1.139	0.0880	0.0436
p-value ($\alpha=0, \beta=1$)	0.052	0.377	0.335	0.229	0.254	0.069	0.152	0.083	0.100	0.011	0.032	0.016	0.001	0.000	0.009	0.001	0.067	0.346	0.781	0.930	0.340	0.916	0.957	
HP T-test ($\gamma=0$)	0.929	0.856	1.285	1.597	0.758	0.576	1.278	1.214	1.138	1.510	1.912*	1.472	2.071**	1.268	1.150	2.188**	2.275**	0.576	0.941	0.695	-0.349	-1.051	-0.430	-0.271
p-value ($\gamma=0$)	0.356	0.395	0.202	0.113	0.450	0.566	0.205	0.229	0.260	0.139	0.064	0.150	0.046	0.214	0.258	0.036	0.029	0.568	0.354	0.494	0.730	0.305	0.672	0.789
Inflation																								
Constant, α	-0.018	-0.024	-0.025	-0.036	0.012	-0.001	-0.004	-0.001	0.004	0.011	0.036***	0.033**	0.046***	0.050***	0.056***	0.049***	0.029	0.009	0.004	-0.003	-0.010	-0.009	0.007	-0.002
p-value ($\alpha = 0$)	0.785	0.706	0.644	0.460	0.445	0.931	0.810	0.923	0.795	0.306	0.007	0.021	0.002	0.001	0.000	0.001	0.104	0.650	0.853	0.836	0.547	0.431	0.635	0.882
IMF Nowcast, β	1.759	1.831	1.828	1.931	1.061	1.183	1.220	1.185	1.157	0.905	0.705*	0.683**	0.697**	0.590**	0.433***	0.495***	0.775	0.822	0.918	1.098	1.215	1.263	1.006	1.160
p-value ($\beta = 1$)	0.434	0.362	0.309	0.255	0.817	0.486	0.452	0.550	0.630	0.418	0.027	0.029	0.027	0.015	0.002	0.009	0.322	0.525	0.780	0.734	0.419	0.239	0.979	0.435
Observations	64	80	94	105	108	104	90	72	56	43	36	35	34	38	33	36	35	32	24	25	22	19	21	
Adjusted R-squared	0.173	0.181	0.181	0.205	0.167	0.191	0.250	0.398	0.409	0.424	0.331	0.313	0.381	0.271	0.148	0.166	0.350	0.413	0.460	0.601	0.575	0.332	0.385	0.533
MZ F-test ($\alpha=0, \beta=1$)	6.100***	4.872**	3.497**	2.362*	1.359	0.570	0.549	0.947	1.639	0.554	4.163**	3.103*	5.699***	6.264***	10.590***	6.514***	1.736	0.253	0.0526	0.0772	0.343	0.759	0.205	0.425
p-value ($\alpha=0, \beta=1$)	0.004	0.010	0.034	0.099	0.261	0.567	0.580	0.393	0.204	0.579	0.024	0.058	0.007	0.005	0.000	0.004	0.192	0.778	0.949	0.926	0.713	0.481	0.817	0.660
HP T-test ($\gamma=0$)	1.959*	2.240**	2.199**	1.925*	1.403	1.068	1.044	1.265	1.508	0.572	2.090**	1.517	2.859***	2.307**	2.016*	1.333	1.071	-0.557	-0.263	0.355	0.369	0.352	0.655	0.593
p-value ($\gamma=0$)	0.055	0.028	0.030	0.057	0.164	0.288	0.299	0.210	0.137	0.570	0.044	0.138	0.007	0.028	0.051	0.192	0.292	0.581	0.794	0.726	0.716	0.521	0.560	

Note:

(1) Robust standard errors in parentheses unless otherwise indicated; *** p<0.01, ** p<0.05, * p<0.1

(2) Mincer Zarnowitz Null: Nowcast is unbiased and efficient

(3) Holden Peel Null: Nowcast is unbiased

Table B.3: Regression Output for Figure 5
 (Nowcast Horizons and Nowcast Accuracy, by month of nowcast, full sample)

	(1) Jan	(2) Feb	(3) Mar	(4) Apr	(5) May	(6) June	(7) July	(8) Aug	(9) Sep	(10) Oct	(11) Nov	(12) Dec
Real GDP Growth												
Constant, α	-0.000	0.017	-0.012*	-0.011	0.011	0.012	-0.002	0.002	0.007	0.002	-0.002	0.010
p-value ($\alpha = 0$)	0.995	0.190	0.100	0.145	0.137	0.126	0.838	0.759	0.105	0.796	0.681	0.172
IMF Nowcast, β	0.913	0.651	1.18	1.045	0.577**	0.832	0.989	1.032	0.907	1.151	0.875	0.554*
p-value ($\beta = 1$)	0.866	0.111	0.210	0.780	0.0122	0.243	0.961	0.839	0.157	0.518	0.113	0.056
Observations	72	28	61	55	50	70	65	33	37	22	33	71
Adjusted R-squared	0.164	0.245	0.573	0.615	0.254	0.410	0.439	0.474	0.661	0.452	0.765	0.379
MZ F-test ($\alpha=0, \beta=1$)	0.582	1.428	1.403	2.905*	3.576**	1.309	0.232	0.157	3.854**	0.324	2.911*	2.038
p-value ($\alpha=0, \beta=1$)	0.561	0.258	0.254	0.0635	0.0357	0.277	0.794	0.856	0.0307	0.727	0.0694	0.138
HP T-test ($\gamma=0$)	-0.675	0.0635	-1.345	-2.382**	-0.570	1.356	-0.602	0.569	0.786	0.800	-1.785*	-1.165
p-value ($\gamma=0$)	0.502	0.950	0.184	0.0208	0.571	0.180	0.550	0.574	0.437	0.432	0.0837	0.248
Nominal GDP Growth												
Constant, α	-0.008	0.052	0.013	0.068***	0.004	0.022**	0.069**	0.045	0.093***	0.007	-0.008	0.020**
p-value ($\alpha = 0$)	0.607	0.108	0.411	0.002	0.818	0.018	0.012	0.198	0.000	0.746	0.371	0.023
IMF Nowcast, β	1.264**	0.744*	0.968	0.714***	0.877	0.965	0.632**	0.662	0.229***	1.094	0.992	0.853**
p-value ($\beta = 1$)	0.0247	0.098	0.748	0.000	0.171	0.325	0.021	0.293	0.000	0.326	0.870	0.0289
Observations	70	28	61	55	50	71	64	33	37	22	33	72
Adjusted R-squared	0.725	0.667	0.677	0.962	0.822	0.969	0.757	0.353	0.764	0.907	0.921	0.637
MZ F-test ($\alpha=0, \beta=1$)	3.557**	1.510	0.473	28.80***	1.520	2.940*	3.367**	0.972	5.908***	1.149	1.046	3.604**
p-value ($\alpha=0, \beta=1$)	0.034	0.240	0.625	0.000	0.229	0.060	0.041	0.389	0.000	0.337	0.363	0.032
HP T-test ($\gamma=0$)	2.146**	0.873	0.689	-0.720	-1.439	1.329	-0.715	-0.209	-1.147	1.492	-1.458	-0.375
p-value ($\gamma=0$)	0.035	0.390	0.494	0.475	0.157	0.188	0.477	0.836	0.259	0.151	0.155	0.709
Inflation												
Constant, α	-0.007	0.034*	0.022*	0.072***	0.051**	0.032	-0.031	-0.013	-0.008	0.017	-0.023*	-0.000
p-value ($\alpha = 0$)	0.866	0.085	0.089	0.009	0.016	0.126	0.447	0.157	0.412	0.574	0.082	0.961
IMF Nowcast, β	1.488	0.563	1.003	0.744***	0.852	1.024	1.388	1.207*	1.047**	1.052***	1.355**	1.037
p-value ($\beta = 1$)	0.488	0.109	0.981	0.000	0.149	0.823	0.405	0.083	0.026	0.000	0.018	0.655
Observations	72	28	61	55	50	69	64	31	37	23	33	72
Adjusted R-squared	0.318	0.260	0.710	0.930	0.446	0.602	0.641	0.910	0.978	0.974	0.876	0.758
MZ F-test ($\alpha=0, \beta=1$)	1.900	1.811	4.672**	23.96***	3.264**	1.235	0.390	1.644	2.862*	39.05***	3.127*	0.125
p-value ($\alpha=0, \beta=1$)	0.157	0.183	0.013	0.000	0.047	0.297	0.679	0.211	0.071	0.000	0.058	0.882
HP T-test ($\gamma=0$)	1.730*	-0.301	2.293**	-0.012	1.771*	1.476	0.831	0.612	-0.009	1.114	1.382	0.484
p-value ($\gamma=0$)	0.088	0.765	0.025	0.991	0.083	0.145	0.409	0.545	0.993	0.277	0.176	0.630

Note:

(1) Robust standard errors in parentheses unless otherwise indicated; *** p<0.01, ** p<0.05, * p<0.1

(2) Mincer Zarnowitz Null: Nowcast is unbiased and efficient

(3) Holden Peel Null: Nowcast is unbiased