Policy Research Working Paper 10406

Data Transparency and GDP Growth Forecast Errors

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WORLD BANK GROUP
Middle East and North Africa Region
Office of the Chief Economist
April 2023

Abstract

This paper examines the role of a country's data transparency in explaining gross domestic product growth forecast errors. It reports four sets of results that have not been previously reported in the existing literature. First, forecast errors—the difference between forecasted and realized gross domestic product growth—are large. Globally, between 2010 and 2020, the average same-year forecast error was 1.3 percentage points for the World Bank's forecasts published in January of each year, and 1.5 percentage points for the International Monetary Fund's January forecasts. Second, the Middle East and North Africa region has the largest forecast errors compared to other regions. Third, data capacity and transparency significantly explain forecast errors. On average, an improvement in a country's Statistical Capacity Index, a measure of data capacity and transparency, is associated with a decline in absolute forecast errors. A one standard deviation increase in the log of the Statistical Capacity Index is associated with a decline in absolute forecast errors by 0.44 percentage point for World Bank forecasts and 0.49 percentage point for International Monetary Fund forecasts. The results are robust to a battery of control variables and robustness checks. Fourth, the role of the overall data ecosystem, not just those elements related to gross domestic product growth forecasting, is important for the accuracy of gross domestic product growth forecasts. Finally, gross domestic product growth forecasts from the World Bank are more accurate and less optimistic than those from the International Monetary Fund and the private sector.

This paper is a product of the Office of the Chief Economist, Middle East and North Africa Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at aislam@worldbank.org.

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Keywords: GDP Growth Forecasts, Forecast Error, Optimism, Economic Outlook, Data Transparency, Statistical Capacity

JEL Codes: C82, E01, E17, E66, O47, O50, R11.

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I. Introduction

Economic forecasts matter for government decisions. They are inputs to the formulation of policies that aim to safeguard and advance economies. Accurate forecasts enhance the possibility of timely and targeted interventions. During the COVID-19 pandemic, short-term growth forecasts have been vital for tracking the impact of the pandemic and the likely trajectory of the recovery—which assists authorities in ascertaining the economic costs of the pandemic and charting the way forward. Growth forecasts affect decisions regarding a host of policies related to spending and debt. Research has shown that overly optimistic forecasts can hurt an economy in the long run. They initially lead to short-run increases in output as bullish governments and businesses increase borrowing and spending. But within a few years the debt load spawns economic contractions (Beaudry and Willems, 2022).[2] This idea is not new. The idea that macroeconomic fluctuations can arise due to difficulty in forecasting was raised by Arthur Pigou as long ago as 1927.

Growth forecasts are used by a wide array of stakeholders. They may guide international organizations such as the World Bank and the International Monetary Fund (IMF) in adapting and setting up lending programs. The private sector may use forecasts to tailor investment strategies or reassess country debt sustainability and debt ratings. Surprises in growth forecast releases tend to move financial markets (Campbell and Sharpe, 2009; Clements and Galvão, 2017). Firms with more optimistic views of their future production prospects tend to be highly leveraged (Jochem and Peters, 2017). Misallocation of resources from over-optimism or pessimism at the firm level can hurt society's economic well-being (Bachmann and Elstner, 2015).

Growth forecasts cannot—and need not—perfectly predict the future. But gross and systematic errors in forecasts may lead policy makers and the private sector astray. Most relevant is the challenge of low data capacity and transparency, a long-standing issue in many countries, particularly developing economies. These data problems impede sound analyses and policy making. This paper focuses on growth forecasts. The paper seeks to unpack the relationship between growth forecast errors and their determinants, with special attention given to the role of data systems.

To study the determinants of growth forecast errors, we rely on time series of growth forecasts published by the World Bank, the IMF, and the private sector between 2010 and 2020. With the benefit of hindsight, we can compute forecast errors by comparing the World Bank and IMF forecasts for a given year with the realized growth rates covering a large number of developing countries. In turn, we estimate regression models where the key explanatory variable is the World Bank's Statistical Capacity Index (SCI). As far as we know, this paper is the first to assess the empirical relationship between growth forecast errors and data systems.

In sum, this paper presents five empirical contributions to the existing literature on macroeconomic forecasting. First, same-year forecast error—the difference between forecast growth and realized growth—is sizable. Globally, between 2010 and 2020, the average same-year forecast error is 1.3 percentage points for the January World Bank's forecasts and 1.5 percentage points for the January IMF's forecasts. Second, the Middle East and North Africa region (MENA) has the largest forecast errors among world regions. Third, on average, improvements in a country's Statistical Capacity Index (SCI), a measure

[2] Using the IMF's WEO data, Beaudry and Willems (2022) found that overestimating annual growth by 1 percentage point over three years reduces real GDP growth three years after that by about 1 percentage point on average.

of data capacity and transparency, are associated with a decline in absolute forecast errors. A one standard deviation increase in the log of SCI is associated with a decline in absolute forecast errors by 0.44 percentage points for World Bank forecasts and 0.49 percentage points for International Monetary Fund (IMF) forecasts. The results are robust to the inclusion of a battery of control variables, such as GDP per capita, institutions, polity, commodity shocks, and armed conflict. Fourth, the role of the overall data ecosystem, not just those elements related to GDP growth forecasting, is important for the accuracy of GDP growth forecasts. Finally, growth forecasts from the World Bank are more accurate and less optimistic than those from the IMF and the private sector. Depending on the specification, the IMF's forecasts are about 0.2 to 0.3 percentage points less accurate and more optimistic than the World Bank's forecasts after controlling for country characteristics.

II. The Conceptual Underpinnings of Forecast Errors

Researchers have long explored the accuracy of macroeconomic forecasts. The key questions they have debated include whether forecasts are unbiased or efficient, whether they depend on the type of forecaster, and whether they are affected by significant economic events such as recessions, by the level of economic development, and by the forecast horizon.

The early literature made the case that forecasts for a range of economic variables in the United States were unbiased (Brown and Maital, 1981; Keane and Runkle, 1990) because on average, the forecast errors were zero (Keane and Runkle, 1990). More recent studies have questioned whether those forecasts are indeed unbiased. Loungani (2001) found that growth forecasts for a broad set of countries are biased: specifically, on average, forecast errors are positive (optimistic), and are more so for developing countries. Ho and Mauro (2016) also uncover optimism bias and find that the bias is greater the longer the forecast horizon.

Nordhaus (1987) made the case that growth forecasts may be inefficient because they do not contain all the information available at the time they are made. Nordhaus found forecasts to be weakly inefficient—that is, forecast revisions were significantly correlated with each other. That suggests that forecasters hold on to prior views for far too long, even as relevant new information emerges. This sluggishness of revisions in growth forecasts has been documented by more recent studies (Loungani et al., 2013). The difficulty in predicting recessions even as they are emerging can also be related to behavioral factors—forecasters may be reluctant to incorporate either good or bad news (Loungani, 2001; An et al., 2018).

The literature has identified several ways through which forecasting errors may manifest. One approach to probing the determinants of forecast errors is to organize them conceptually into four categories: lack of information, structural volatility, exogenous shocks, and forecaster capacity and bias. Our paper's main contribution is the role of data capacity and transparency.

Lack of information: Forecasts are as good as the information supporting them. To our knowledge, our paper is the first to rigorously examine the hypothesis that a country's data capacity and transparency plays an important role in explaining forecast errors. This is the main contribution of our paper. Eicher et al. (2019) found large forecast errors in developing economies and suggest that lower quality data may be responsible.

Structural volatility: Countries may be exposed to internal and external factors that induce larger-than-anticipated economic changes. Such exposure increases the volatility of economic growth, which makes it more difficult to forecast accurately. Commodity-price and external-debt-financing shocks are prominent sources of such volatility. Several institutional factors could also lead to macroeconomic volatility. Growth in countries that frequently face conflict and social upheaval may be harder to forecast accurately, given the large macroeconomic effects of conflict (Novta and Pugacheva, 2021). Smaller economies may be more volatile than larger economies because they are more vulnerable to shocks. Volatility is hard to anticipate and incorporate in forecasting models, leading to larger forecast errors. Developing economies, which might be less diversified and depend on the vagaries of commodity prices, may be exposed to large shocks that can cause large forecast errors (Eicher et al., 2019). In our paper, they are controlled in the econometric analyses.

Exogenous external shocks: Unanticipated natural disasters or global shocks, such as the COVID-19 pandemic, may cause significant forecast errors. A sudden, large external shock whose effects are unknown can lead to incorrect forecasts across the board. The inability to account for these typically adverse shocks due to uncertainty of the effects can result in optimistic forecasts. Some evidence of this was observed at the onset of the COVID-19 pandemic—these resulted in conflicts between forecasts and policy prescriptions. For example, Sandefur and Subramanian (2020) found that early in the pandemic growth forecasts by international organizations appeared to suggest the effect of the COVID-19 shock would be muted, while the international organizations themselves pushed for broad policy action to address what they perceived as the substantial pandemic impact. In our paper, they are controlled for with year fixed effects, a proxy for global shocks.

Forecaster capacity and bias: The accuracy of forecasts may depend on characteristics specific to a forecaster. Forecasting models may be incorrect—also called model uncertainty (Beckman, 1992). Forecasting models may underestimate fiscal multipliers in their assumptions (Blanchard and Leigh, 2013). Some forecasters could be systematically optimistic or pessimistic (Beaudry and Willems, 2022). Some forecasters may have channels of communication with policy makers. If an economy grows above the long-term trend for a short period, it may trigger exuberant optimism among policy makers that feeds back into forecaster models, yielding a policy optimism bias. Alternatively, it may be that an optimism bias occurs because forecasters are unable to forecast recessions (An et al., 2021). Furthermore, conflicts of interest may arise when there is a business relationship between forecasters and governments. Institutions that have government clients or central banks that have little independence are susceptible to making forecasts biased in favor of appeasing clients.[3] Our paper shows that forecasts from the World Bank are on average more accurate and less optimistic than forecasts from the IMF or the private sector.

The literature is inconclusive on how forecast errors vary by government, international institutions, and private forecasters. Nordhaus (1987) found that the correlation between forecast revisions—a measure of forecast stickiness—were highest (stickier) for international agencies (institutional forecasts) and lowest for professional (private) forecasters. Morikawa (2020) found that economic growth forecasts are less upwardly biased for academic researchers than professional forecasters in private institutions and governments. However, the disparity between private and international institutional forecasts is not confirmed by other studies. An et al. (2021) investigated short-term growth projections from all major

[3] There is a sizeable literature that has explored the effects of conflicts of interest. In financial markets, studies have shown that such conflicts have led to biases in equity analysts' stock recommendations and earnings forecasts (Malmendier and Shanthikumar, 2007; Hong and Kacperczyk, 2010). Conflicts of interest also arise in credit rating agencies when they must rate their customers (Mathis et al., 2009; Griffin and Tang, 2012). Fabo et al. (2020) showed that central bank papers report larger effects on output and inflation from quantitative easing (QE) than do papers by academic economists. Central bankers who report larger QE effects on output are found to have more favorable career outcomes, indicating considerable involvement of bank management in the research process. These biases are somewhat reduced because professional forecasters are also influenced by a desire to protect their reputations.

institutions and the private sector and found that there is a high degree of collinearity across the forecasts—across international institutions and the private sector, the forecasts made at a given time period for a given country and year tend to be similar.

III. Data and Empirical Specifications

The main data sources for GDP growth forecasts are the same-year growth forecasts made in January by the IMF's *World Economic Outlook* (WEO) and the World Bank's *Global Economic Prospects* (GEP).[4] Growth forecasts by these international institutions are widely used by authorities to assess economic prospects, benchmark their own projections, and are also used by private-sector forecasters (Genberg and Martinez, 2014; Genberg, Martinez, and Salemi, 2014; Beaudry and Willems, 2022).[5] In addition, we explore same-year growth forecasts made in April, June and October by the WEO; one-year-ahead and two-year-ahead growth forecasts made in January by the GEP. Supplementary data include same-year growth forecasts made in January by the private sector obtained from Consensus Forecasts (all countries except MENA countries) and Focus Economics (for MENA countries only).[6]

For our baseline regression analysis that includes the main covariates, we use a common sample that covers the same set of 126 countries from 2010 to 2020 in the World Bank GEP January Forecasts sample for same-year forecasts and the IMF WEO January Forecasts sample for same-year forecasts. Private sector consensus (average) January Forecasts sample for same-year forecasts have much lower coverage resulting in 56 countries from 2015 to 2020 in the baseline regression with the main covariates.

III.1.Forecast Errors

Data from the common sample of the IMF's WEO and the World Bank's GEP shows that globally, between 2010 and 2020,[7] the average same-year GDP growth forecast error—the difference between forecasted GDP growth and realized GDP growth—is 1.3 percentage points for the January GEP forecasts and 1.5 percentage points for the January WEO forecasts. In other words, on average, GEP's growth forecasts in January are 1.3 percentage points higher than the realized growth for that year, while WEO's growth forecast in January is 1.5 percentage points higher. When 2020 is excluded, the global average forecast error is 0.4 of a percentage point for the January GEP forecasts and 0.7 of a percentage point for the January WEO forecasts. The MENA region on average had the largest forecast errors among all global regions between 2010 and 2020 (see Figure 1, Panel A). The MENA region has the largest growth forecast

[4] For more information on the World Bank's *Global Economic Prospects* reports, visit https://www.worldbank.org/en/publication/global-economic-prospects or https://openknowledge.worldbank.org/handle/10986/2140; for more information on the International Monetary Fund's *World Economic Outlook* reports, visit https://www.imf.org/en/Publications/WEO.

[5] Evidence on the importance of WEO forecasts has been summarized in Beaudry and Willems (2022). About 88 percent of country authorities strongly agree with the statement that that they "consider the WEO's projections to be the benchmark for assessing economic prospects." Furthermore, 64 percent of country authorities strongly agreed with the statement that they "use WEO forecasts to check the accuracy of [their] own forecasts," while 75 percent strongly agreed that "WEO forecasts are valuable inputs to the economic policy process in [their] country."

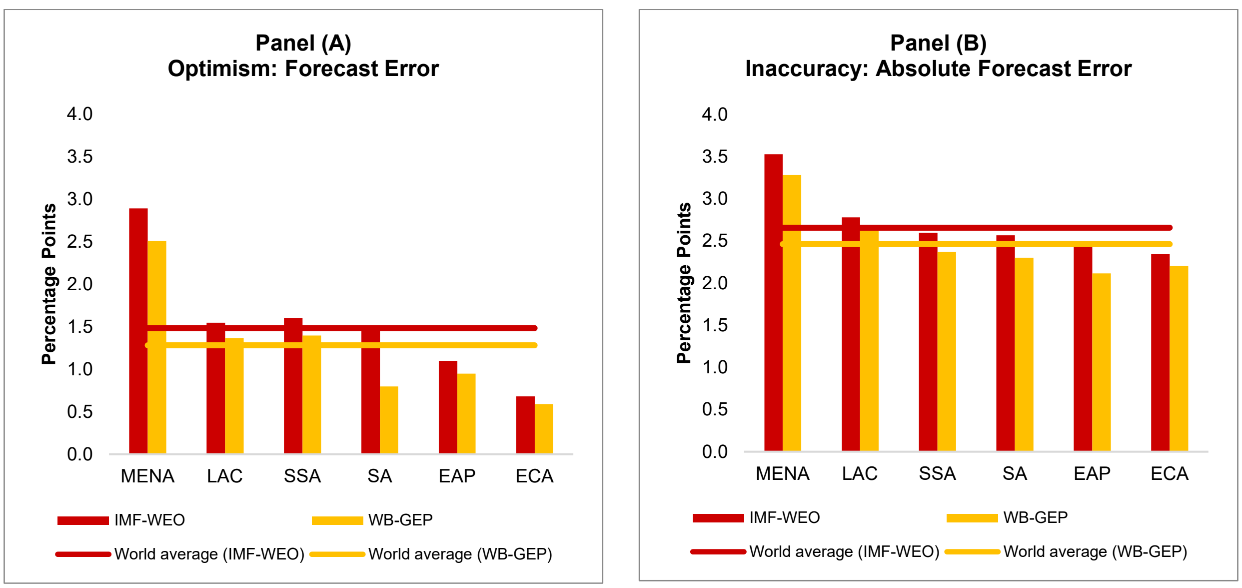
[6] For more information on Consensus Forecasts, visit https://www.consensuseconomics.com/; for more information on Focus Economics Forecasts, visit https://www.focus-economics.com/regions/middle-east-and-north-africa.

[7] The analysis focuses analyses on 2010–2020 because systematic World Bank January GEP forecast data are only available for this period. Note that in the paper, we do not provide trends of the private sector's forecasts given their limited coverage of countries and years.

errors, averaging 2.5 percentage points for the January GEP forecasts and 2.9 percentage points for the January WEO forecasts. These are quite large given that the MENA average growth rate for this period was only 1 percent. The positive forecast errors are indicative of an optimism bias—institutional forecasters tend to predict higher growth rates than are realized. For lack of a better term, we refer to forecast errors as the degree of "optimism bias."[8] Optimism bias is consistent across all regions, although it is largest in the MENA region.

A similar story emerges for the absolute GDP growth forecast errors, which is the absolute value of the difference between GDP growth forecasts and realized GDP growth. In other words, absolute forecast errors remove the direction of the bias and hence reflect the accuracy of the forecasts. Globally, the absolute forecast error is 2.5 percentage points for the January GEP forecasts and 2.7 percentage points for the January WEO forecasts. It is also the largest for the MENA region (see Figure 1, Panel B). We refer to absolute forecast errors as the "inaccuracy" of the forecasts. Both forecast errors and absolute forecast errors appear not to vary systematically by a country's level of income, at least for the sample in this study. The MENA region stands out with its high forecast errors, which are not dependent on the level of development. Both panels in Figure 1 indicate that growth forecasts from the IMF's WEO are slightly more optimistic and more inaccurate than growth forecasts from the World Bank's GEP, for all regions. Note that the panels are constructed from a common sample of the IMF's WEO and World Bank's GEP, so the findings are not driven by differences in the sample composition. These results are confirmed by more rigorous econometric estimations in Sections IV and V.

Figure 1. January Same-Year GDP Growth Forecast Errors by Region and Institution (2010–2020)



Source: Authors' calculations based on the International Monetary Fund's January *World Economic Outlook* (WEO) and the World Bank's January *Global Economic Prospects* (GEP).
Note: The figure displays the same-year January GDP growth forecast errors (Panel A) and same-year absolute GDP growth forecast errors (Panel B) of the IMF's *World Economic Outlook* and the World Bank's *Global Economic Prospects*. Forecast errors are calculated as the forecasted GDP growth rates minus realized GDP growth rates. Absolute forecast errors are calculated as the absolute value of the forecast errors. The figure is constructed based on a common sample of 141 countries (largely developing economies) collected in January for each year between 2010 and 2020. The MENA region includes both GCC and non-GCC countries.

MENA also stands out as the region with highest forecast error and absolute forecast error from the private sector's growth forecasts. Appendix Figure A1 shows average GDP growth forecast errors (Panel

[8] Forecast errors can be the result of factors other than optimism bias, such as unforeseen shocks.

A) and absolute GDP growth forecast errors (Panel B) from private forecasters. However, same-year growth forecast data from private sector forecasters are available only since 2015 and for a smaller set of countries. On average, between 2015 and 2020, the average same-year forecast error from the private sector is 1.7 percentage points, while the average same-year absolute forecast error is about 2.4 percentage points (Appendix Figure A1), not too far off the GEP's figures. The forecast error and absolute forecast error are also largest for MENA: about 2.8 and 3.4 percentage points on average respectively.

The timing of forecasts also matters. Appendix Figure A2 using same-year GDP growth forecasts from January, April, June and October from the WEO shows that forecast errors for the year tend to fall in magnitude and increase in precision as the forecasting month shifts from January to October. As the forecasting date approaches the end of the year, forecasters have more information and can thus more accurately forecast growth for that year. Utilizing a longer time series, Appendix Figure A3 visualizes the IMF's April and October GDP growth forecast errors from 1990 to 2020 and finds that the October forecast errors are generally lower.

The longer the forecast horizon, the larger the forecast errors and absolute forecast errors. Appendix Figure A4 shows the GEP's one-year and two-year ahead GDP growth forecast errors and absolute GDP growth forecast errors. Two-year ahead forecast errors and absolute forecast errors are larger than one-year ahead ones. In turn, one-year ahead ones are larger than same-year ones. This feature holds even when we impose the same sample size for different horizons (see Appendix Table A1). This finding is consistent with prior results reported by Ho and Mauro (2016).

III.2. Data Capacity and Transparency

The main variable of interest in our paper, data capacity and transparency, is proxied by the World Bank's Statistical Capacity Index (SCI). The overall SCI score is based on a diagnostic framework to assess the capacity of national statistical systems over time. The framework has three dimensions: source data; methodology; and the periodicity and timeliness of socioeconomic indicators. A composite score for each dimension and an overall score combining all three dimensions are derived for each country on a scale of 0–100. A score of 100 indicates that the country meets all criteria. Each dimension is evaluated on criteria based on metadata information obtained from the World Bank, International Monetary Fund, United Nations, the UN Educational, Scientific and Cultural Organization (UNESCO), and the World Health Organization (WHO).

The overall SCI score is the average of the three sub-indicators calculated for each dimension (see Table 1). The source data dimension reflects whether a country conducts data collection activity in line with internationally recommended frequency (periodicity), and whether data from administrative systems are available and reliable for statistical estimation purposes. This dimension covers the micro-data aspect of data transparency because microdata is at the foundation of a country's data system. Specifically, the criteria used are the frequency of population and agricultural censuses and of poverty- and health-related surveys, and completeness of vital registration system coverage. A country can achieve a perfect score if it has conducted at least one population census in the past 10 years, one or more agricultural censuses in the past 10 years, three or more health surveys in the past 10 years, and has a complete vital registration system.

The statistical methodology dimension measures a country's ability to adhere to internationally recommended standards and methods. This aspect assesses guidelines and procedures used to compile macroeconomic statistics and for social data reporting and estimation practices. This dimension measures the quality of the data system. Under the assumption that international guidelines provide the benchmark for ideal data systems, adherence to such standards implies that the quality of data systems meets well-established standards. Countries are evaluated against a set of criteria such as use of an updated national accounts base year, use of the latest balance of payments manual, the external debt reporting status, an updated consumer price index, an updated industrial production index, updated import/export prices, an accounting basis for reporting government financial data, vaccine reporting to WHO (discrepancy between WHO and government estimates), subscription to the IMF's Special Data Dissemination Standard, and enrollment data reporting to UNESCO). Each criterion has equal weight.

The periodicity and timeliness dimension measures the availability and frequency of key socioeconomic indicators, of which nine are indicators of Millennium Development Goals (MDG). This dimension attempts to measure the extent to which data are made accessible to users through transformation of source data into timely statistical outputs. The frequency of the main indicators considered, each receiving equal weight, includes: an income poverty indicator; a child malnutrition indicator; a child mortality indicator; an immunization indicator; an HIV/AIDS indicator; a maternal health indicator; a gender equality in education indicator; a primary-school completion indicator; an access to water indicator; and a GDP growth indicator.

Table 1. Subcomponents of the Statistical Capacity Indicator

Dimension	Definition
Statistical Methodology (scale: 0-100)	Measures a country's ability to adhere to *internationally recommended standards and methods*. This aspect is captured by assessing guidelines and procedures used to compile macroeconomic statistics and social data reporting and estimation practices.
Source Data (scale: 0-100)	Reflects whether a country conducts *micro data collection* activity in line with internationally recommended frequency and whether *data from administrative systems* are available and reliable for statistical estimation purposes.
Periodicity and Timeliness (scale: 0-100)	Measures *the availability and periodicity of key socioeconomic indicators*, of which nine are Millennium Development Goals (MDG) indicators.

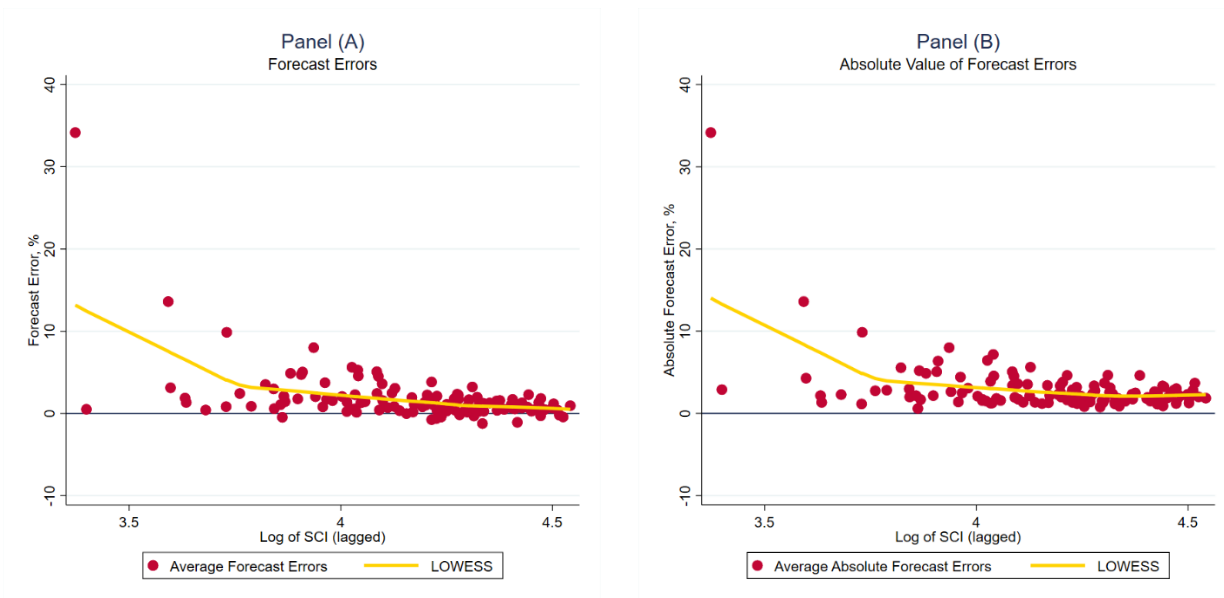
Source: Statistical Capacity Indicator Note, World Bank's Development Data Group (2021).

The World Bank's SCI goes beyond its name by capturing many of the elements of transparency. The availability and regular publication of micro and macro data as well as whether production of such data adheres to international standards goes to the heart of "openness," the ability of citizens to learn information from the government. The measure goes beyond statistical capacity—the SCI score of highly competent statistical offices can be penalized if they do not publish statistics. The SCI captures transparency by using data-centric, objective, and verifiable measures—and is unique in that it is not dependent on perceptions of transparency by survey respondents, as is typically the case in many transparency indicators. The SCI can be interpreted as a statistical or data transparency index.

Several studies have used the SCI to evaluate the quality of data systems and investigate its relationship with other macroeconomic variables (Devarajan, 2013; Kubota and Zeufack, 2020; Islam and Lederman, 2020). Nevertheless, the SCI has limitations. It covers only developing economies and is available from 2004 to 2020. The availability of data at high frequencies (quarterly and monthly) is largely not considered. For microdata, it does not consider establishment and labor force surveys. It also does not include a measure of openness in terms of online access to data. Its successor, the Statistical Performance Indicators (SPI)—launched in *World Development Report 2021: Data for Better Lives*— deals with many of these drawbacks. The SPI measures the capacity and maturity of national statistical systems by assessing the use of data, the quality of services, the coverage of topics, the sources of information, the infrastructure and availability of resources. The SPI covers both developing and advanced economies. However, the SPI is available only for a limited period, 2016-2019. Furthermore, the SPI is still in development, with measurement pending for some elements in its conceptual framework. The correlation between the SCI and SPI is 0.86 for the sample of overlapping developing economies (132) and time periods (2016-2019). The main findings of this paper largely stand whether the SCI or the SPI is used.

A descriptive (unconditional) look at the data reveals that forecast errors tend to be larger for economies with weaker data systems. Weak data systems are characterized by scarce data, low-frequency data, or data of poor quality. Figure 2 presents the correlation between the SCI and both forecast errors and absolute forecast errors for a cross-section of 133 economies with data available in 2020.[9, 10] The figure shows that lower SCI scores are correlated with higher forecast errors. The relationship is especially strong for countries with low SCI, but it still holds for countries with high SCI. In other words, growth forecasts for countries with weaker data systems are on average more optimistic and more inaccurate.

Figure 2. GDP Growth Forecast Errors and Data Capacity Index (SCI)



Source: Authors' calculations based on the World Bank's *Global Economic Prospects*, January issues 2010–2020 and the World Bank's *Statistical Capacity Index*.
Note: The figure displays the correlation between same-year World Bank GEP January forecast errors and the Statistical Capacity Index using LOWESS smoothing. The GDP growth forecast errors are calculated based on forecasted and realized GDP growth rates and are based on a sample of 133 developing countries between 2010 and 2020.

III.3 Other Data

[9] The correlation is presented by locally weighted scatterplot smoothing (LOWESS). The advantage of LOWESS is that it does not require the imposition of a functional form for the relationship between two variables.
[10] Figure 2 largely includes developing economies. However, the correlation between SPI (which is global in coverage) and forecast errors shows similar results.

Other data used in our analysis include commodity export price shocks, conflict, population and income per capita.

The commodity export price shocks data is a comprehensive database of country-specific commodity price shocks created by Gruss and Kebhaji (2019). A commodity export price shock for each country is the combination of changes in international prices of up to 45 commodities and the country's exposure to these commodities' exports (as share of GDP). The weights of each commodity can be fixed weights (based on average exports over GDP over several decades) or time-varying weights (which can account for time variation in the mix of commodities traded and the overall importance of commodities in economic activity). We used fixed weights in our regressions, although using time-varying weights yields consistent results.

Conflict data are from the UCDP/PRIO Armed Conflict Version 21.1 Dataset. This is a dataset that tracks all country-year pairs when conflict occurred, having at least 25 deaths in a given year, from 1946 to 2020. The dataset covers 4 types of conflict: extra-systemic (any conflict between a state a non-state entity outside the territory of the state in question), interstate (any conflict between two states), intrastate (any conflict between a government and non-government entity on the same territory of the government) and finally internationalized intrastate (any intrastate conflict that also includes foreign government intervention). For our paper, we have focused on internal conflict, that is captured through intrastate and internationalized intrastate conflict. A dummy variable is created to identify the country-year pairs when either of these types of conflict occur.

Population and GDP per capita data are from the World Bank's World Development Indicators (WDI) Dataset. They are a proxy for country size and the level of economic development in a country, respectively. GDP growth rates used to measure growth volatility and indicate years of economic booms are also obtained from the WDI Dataset.

Table 2 presents summary statistics for all the variables of interest. In addition, summary statistics of longer-horizon forecasts are also included. It is interesting to note that the longer the horizon of forecasts, the larger forecast error and absolute forecast error. For example, the average GEP's same-year one-year ahead and two-year ahead forecasts error are 1.3, 1.8 and 2.6 percentage points respectively. Even when we restrict them to have the same sample (in Appendix Table A1), the same results hold. This finding is consistent with those in Ho and Mauro (2016).

Table 2. Summary Statistics

Variables	Number of countries	Number of Observations	Mean	Standard Deviation	Median	Min	Max
WB-GEP Forecast Error (January) T	126	1242	1.2	4.4	0.3	-12.4	63.5
WB-GEP Absolute Value of Forecast Error (January) T	126	1242	2.4	3.9	1.2	0	63.5
IMF-WEO Forecast Error (January) T	126	1242	1.4	4.4	0.5	-11.4	42.2
IMF-WEO Absolute Value of Forecast Error (January) T	126	1242	2.6	3.8	1.4	0	42.2
WB-GEP Forecast Error (January) T+1	125	1114	1.7	4.1	0.7	-12.4	33.2
WB-GEP Absolute Value of Forecast Error (January) T+1	125	1114	2.7	3.5	1.5	0	33.2
WB-GEP Forecast Error (January) T+2	121	681	2.6	4.5	1.3	-19.5	28.7
WB-GEP Absolute Value of Forecast Error (January) T+2	121	681	3.3	4.0	1.8	0	28.7
Consensus/Focus Economics Forecast Error (January) T	56	326	1.7	4.3	0.4	-8.7	32.2
Consensus Absolute Value of Forecast Error (January) T	56	326	2.5	3.9	1.0	0.02	32.2
Log of Overall Average SCI Score (lagged)	126	1242	4.22	0.2	4.2	3.3	4.6
Log of GDP Per Capita (Constant 2010 US$) (lagged)	126	1242	7.9	1.0	8.1	5.3	9.8
Export Commodity Price Shocks (T)	126	1242	-0.001	0.03	0	-0.3	0.1
Absolute Value of Export Commodity Price Shocks (T)	126	1242	0.01	0.03	0.01	0	0.3
Internal Conflicts Shocks Dummy (T)	126	1242	0.2	0.4	0	0	1
Log of Total Population (lagged)	126	1242	16.2	1.8	16.2	11.2	21.1
Boom Dummy =1 if Above 10-year Rolling Median Growth (lagged)	126	1242	0.4	0.5	0	0	1
Growth Volatility (Rolling GDP Growth Rate Sd - 10 years) (lagged)	126	1242	3.2	2.7	2.6	0.3	45.7
Log of Overall Average SPI Score (lagged)	165	655	4.096	0.294	4.109	2.97	4.503
Log of SCI-GDP Transparency Direct (lagged)	126	1240	-0.7	0.5	-0.5	-2.7	0
Log of SCI-GDP Transparency Indirect (lagged)	126	1240	-0.5	0.4	-0.3	-1.4	0
Log of SCI-GDP Transparency Other (lagged)	126	1240	-0.3	0.2	-0.3	-1.2	0
Rule of Law (lagged)	116	1044	-0.5	0.6	-0.5	-1.9	1.4
Polity (lagged)	116	1044	3.9	5.4	6	-9	10
Informality (lagged)	116	1044	52.7	23.5	51.1	4.0	95.1
Natural Disasters Shocks Dummy (T)	116	1044	0.04	0.2	0	0	1

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *Statistical Performance Indicators,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict, the World Bank's *Worldwide Governance Indicators,* Polity5 dataset version 2018 from the Center for Systemic Peace, and the EM-DAT (The International Disaster Database).
Note: GDP growth forecast errors are calculated as the forecasted GDP growth rates minus realized GDP growth rates. Absolute growth forecast errors are calculated as the absolute value of the forecast errors. The summary statistics are based on the sample of the main regression results. Variables used in robustness checks or extensions of the main results may have fewer observations than the main regression results.

Additional robustness checks of our models required data on institutions, informality and natural disasters. Data on the quality of institutions were obtained from the Polity5 Regime Authority Characteristics and Transitions Dataset by the Center for Systemic peace, mainly the Polity Index, as well as the Rule of Law Indicator from the World Bank's World Governance Indicators. Informality is proxied by the share of "self-employed" individuals in total employment from ILO estimates. Finally, a natural disaster occurrence dummy was created using the EM-DAT's International Natural Disaster Database created by the Center for research on Epidemiology of Disasters.

III.4 Empirical Specification of the Baseline Regression

In the baseline regressions, the relationship between statistical capacity and the magnitude of same-year forecast errors is explored using two models across three different samples of forecasters. The first sample is from the World Bank's *Global Economic Prospects* January Forecasts (GEP), the second sample is from the International Monetary Fund's *World Economic Outlook* January Forecasts (WEO). Both samples cover the same 126 countries from 2010 to 2020. A panel model is estimated using the absolute value of GDP growth forecast error of same-year forecasts as the outcome variable regressed on the lagged log of statistical capacity and other covariates as presented in equation (1):

$$AbsFcstErr_{i,t} = \alpha + \beta_1\, LogSCI_{i,t-1} + \beta_2\, LogGDPpc_{i,t-1} + \beta_3\, Abs\Delta LogExpPrices_{i,t} + \beta_4\, InternalConflict_{i,t} + \beta_5\, LogPop_{i,t-1} + \beta_6\, Boom_{i,t-1} + \tau_t + \varepsilon_{i,t} \quad (1)$$

Where i is for country and t is for year. The dependent variable is the absolute value of GDP growth forecast errors ($AbsFcstErr$), defined as forecasted GDP growth minus actual GDP growth. A negative forecast error signifies that forecasted GDP growth was below actual GDP growth. The main regressor is the log of lagged Statistical Capacity Index ($LogSCI$), as measured by the World Bank Statistical Capacity Indicator (SCI). Following Eicher et al. (2019), we expect lower quality data to drive larger forecast errors. The identification strategy leverages cross-country variation across time in both forecast errors and the SCI. There are two main concerns of endogeneity. One is the possibility of simultaneity bias or reverse causality. It seems unlikely that the forecast errors will affect the quality of the data systems. However, one cannot rule out the possibility that as a response to growth forecast errors, policy makers may enact reforms to improve data systems. To limit this, we use the lagged value of the SCI. The second concern is that of omitted variable bias. We address this by accounting for as many relevant covariates as possible, as discussed below. We cannot completely obviate the endogeneity concerns in the study, but we do alleviate them as much as possible.

To account for omitted variable bias, explanatory variables employed include several covariates. The log lagged GDP per capita in constant 2010 US dollars ($LogGDPpc$) is included as a proxy for the level of economic development. According to Loungani (2001), on average, forecast errors are positive (optimistic), and more pronounced in developing countries. Due to their greater susceptibility to shocks, smaller economies may exhibit greater volatility than larger ones. Developing economies may be more susceptible to severe shocks that might result in significant forecast errors since they may be less diversified and dependent on the fluctuations of commodity prices (Eicher et al., 2019). Therefore, we include the lagged log of the total number of population in an economy ($LogPop$) as a proxy for country size, and the absolute value of log change in export commodity prices ($Abs\Delta LogExpPrices$), which captures both exposure to commodity exports and the fluctuations of the international prices. An internal conflict dummy variable ($InternalConflict$) for internal conflict country-year pairs - as defined using the UCDP-Prio Dataset is included in our analysis. Given the significant macroeconomic repercussions of conflict, growth in countries that frequently experience conflict and social unrest may be more difficult to forecast with accuracy (Novta and Pugacheva, 2021). We also include a lagged dummy variable for economic booms ($Boom$) which is a dummy variable if growth is greater than or equal to the previous 10-year median growth. Frankel (2011) found that official forecasters tend to be overly optimistic during booms and busts, more so than when GDP is at its long-run trend. They overestimate the durability of booms and underestimate the transitory nature of busts (Frankel, 2011). Recessions are more difficult for forecasters to foresee (Eicher et al., 2019). It is plausible that an optimism bias emerges as a result of forecasters' inability to predict recessions (An et al., 2021). Even as pertinent new information is revealed, forecasters hold onto prior views for far too long (Loungani et al., 2013). Finally, τ_t is the year fixed effect, accounting for global shocks, and $\varepsilon_{i,t}$ is the error term. Note that $LogSCI_{i,t-1}$; $LogPop_{i,t-1}$ and $Boom_{i,t-1}$ belong to the information set available to forecasters at the time of forecast (January of each year). $Abs\Delta LogExpPrices_{i,t}$ and $InternalConflict_{i,t}$ are new developments in the year of the forecast that forecasters might not foresee. Hence, they can explain forecast error.

Many other explanatory variables—such as institutions, polity, informality, and natural disasters—are considered as part of the robustness checks in Section VI. They are not included here as they do not affect the main results and do not have much explanatory power. They also entail a drop in observations in some cases, and thus we opted for a more parsimonious specification. Note that country fixed effects are not included because $LogSCI$ is a slow-moving variable and is largely absorbed into the country fixed effects when included. This is a concern as we are unable to account for all time-invariant country-specific omitted variables. Thus, we account as for many variables in the literature that have been theoretically linked to growth forecast errors.

The volatility of GDP growth rates is another variable that may affect growth forecast errors. Lewis and Pain (2014) found that when forecast errors are adjusted for the significant cross-country variations in average GDP growth rates and GDP growth volatility, differences in forecasting performance among OECD countries tend to diminish. From the late 1970s through the middle of the 2000s, the G7 economies' average absolute forecast error dropped. This is due in part to the moderation of GDP growth volatility. Shorter-term declines may also be a result of better data availability, particularly for near-term developments, and better forecasting methods. These findings are supported by Turner (2016), who also noted that the decrease in GDP growth volatility and possibly improved accessibility and timeliness of national accounts data and other hard indicators are likely to contribute to the trend improvement in current-year forecasting performance in OECD countries over the period 1971–2012. Therefore, we run an additional set of estimations including GDP growth volatility as a covariate, which is measured as the lagged rolling 10-year standard deviation of realized GDP growth rates. Growth volatility is correlated with a number of covariates, and therefore we include it in a separate sect of regressions to uncover what factors may be affecting forecast errors through the growth volatility channel.

Additionally, equation 1 is re-estimated with forecast errors as the outcome variable ($FcstErr$) to analyze forecast optimism. An additional adjustment is that the lagged log of change in export commodity prices ($\Delta LogExpPrices$) is used in equation 2 instead of its absolute value in equation 1, to capture the direction of the price shock (see equation 2).

$$FcstErr_{i,t} = \alpha + \beta_1 \, LogSCI_{i,t-1} + \beta_2 \, LogGDPpc_{i,t-1} + \beta_3 \, \Delta LogExpPrices_{i,t} + \beta_4 \, InternalConflict_{i,t} + \beta_5 \, LogPop_{i,t-1} + \beta_6 \, Boom_{i,t-1} + \tau_t + \varepsilon_{i,t} \quad (2)$$

IV. Main Findings: Growth Volatility, Data Transparency and Forecast Errors

As previously indicated, growth forecast errors are analyzed for three samples: (i) the World Bank's GEP January forecasts (2010-2020); (ii) the IMF's WEO January forecasts (2010-2020); and (iii) the January Consensus/Focus Economics private forecasts (2015-2020). Results for the World Bank GEP sample are presented in column 1 of Table 3. Column 2 presents the regression results for the IMF WEO sample, and column 3 presents the results for the Consensus/Focus Economics private forecaster sample. Columns 4 through 6 replicate columns 1 through 3 with the inclusion of growth volatility as an additional independent variable (a covariate).

Growth forecasts are more accurate in countries with better data ecosystems. The quality of the data ecosystem (SCI) is negatively correlated with the absolute growth forecast errors (Table 3). This is consistent across World Bank, IMF, and private sector forecast errors. The magnitude is economically significant. In the base regression, the coefficient of -2.213 in column (1) implies that when the log of SCI improves by one standard deviation, same-year absolute forecast errors by the World Bank are lower by 0.44 percentage points. For the IMF, the corresponding figure is 0.49 percentage points. The coefficient of private-sector forecasters is statistically insignificant at the 10 percent level but retains a large magnitude despite a small sample size. Forecasters have more and better information in countries with better data ecosystems, leading to lower forecast errors.

The quality of the data ecosystem remains a strong predictor of forecast accuracy even after accounting for growth volatility, despite both being interrelated across all three samples (columns 4, 5 and 6).

Table 3. Determinants of Absolute GDP Growth Forecast Errors (Forecast Accuracy)

	Base Model			With Growth Volatility		
Y = Absolute Value of Forecast Errors	**WB-GEP (2010-2020)**	**IMF-WEO (2010-2020)**	**Consensus/ Focus Economics (2015-2020)**	**WB-GEP (2010-2020)**	**IMF-WEO (2010-2020)**	**Consensus/ Focus Economics (2015-2020)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log of SCI (lagged)	-2.213*	-2.426**	-1.940	-1.408**	-1.595***	-1.799
	(1.189)	(1.056)	(1.606)	(0.599)	(0.529)	(1.510)
MENA Dummy	0.906	1.032	1.095	0.634**	0.750**	1.157*
	(0.667)	(0.689)	(0.749)	(0.310)	(0.362)	(0.635)
Growth Volatility (lagged)				0.392***	0.404***	0.293***
				(0.141)	(0.112)	(0.078)
Log of GDP Per Capita (lagged)	0.273	0.258	-0.109	0.112	0.092	-0.178
	(0.183)	(0.187)	(0.395)	(0.097)	(0.110)	(0.316)
Absolute Value of Export Commodity Price Shocks (T)	1.677	4.172	8.017	-1.501	0.892	5.383
	(4.788)	(5.126)	(9.283)	(3.993)	(4.596)	(9.831)
Internal Conflicts Shocks Dummy (T)	0.367	0.191	0.389	0.022	-0.165	-0.100
	(0.293)	(0.320)	(0.396)	(0.204)	(0.232)	(0.428)
Log of Total Population (lagged)	-0.188***	-0.168***	-0.224**	-0.123**	-0.101*	-0.105
	(0.055)	(0.064)	(0.106)	(0.054)	(0.058)	(0.101)
Boom Dummy =1 if Above Median Growth (lagged)	-0.165	-0.309*	-0.642**	-0.166	-0.310*	-0.513**
	(0.182)	(0.170)	(0.246)	(0.197)	(0.171)	(0.232)
Constant	11.966***	13.195***	14.636**	7.773***	8.868***	11.873**
	(3.913)	(3.726)	(6.856)	(2.084)	(2.097)	(5.636)
Number of observations	1,242	1,242	326	1,242	1,242	326
R2	0.345	0.318	0.489	0.413	0.392	0.504
Adjusted R2	0.336	0.308	0.469	0.405	0.383	0.484
Number of Countries	*126*	*126*	*56*	*126*	*126*	*56*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.

Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. Columns (1) and (4) samples refer to same-year World Bank GEP January Forecasts sample from 2010 to 2020, covering 126 countries. This common sample is used to define the columns (2) and (5) samples, for same-year IMF-WEO January Forecasts from 2010 to 2020. Columns (3) and (6) samples refer to same-year Consensus January Forecasts and the MENA region Focus Economics January Forecasts, from 2015 to 2020, covering 56 countries, and are not forced to be a common sample with WB-GEP and IMF-WEO. Log of SCI (lagged) is the one-year lagged log of Statistical Capacity Indicator. Growth Volatility (lagged) is the one-year lagged rolling 10-year standard deviation of realized growth rates. Log of GDP Per Capita (lagged) is the one-year lagged log of GDP per capita in constant 2010 US dollars. Absolute Value of Export Commodity Price Shocks (T) is the same-year absolute value of the log change in export commodity prices, it captures both exposure to commodity exports and the fluctuations of the international prices. Internal Conflicts Shocks Dummy (T) is the same-year dummy variable for internal conflict country-year pairs - as defined using the UCDP-Prio Dataset. Log of Total Population (lagged) is the one-year lagged log of population and is considered a proxy for the country size. Boom Dummy if Above Median Growth (lagged) is a one-year lagged dummy variable for economic booms if growth is greater than or equal to the previous 10-year median growth. Note that the unforeseen shocks taken into account in this regression occurred during the same year of the forecast, after the GDP growth forecasts were published in January.

The coefficient of growth volatility, measured as the standard deviation of GDP growth (lagged rolling 10-year average), is positive and statistically significant at the 1 percent level across the three samples (see columns 4, 5, and 6). As expected, countries experiencing larger growth volatility have larger absolute forecast errors. Commodity price shocks and internal conflict shocks are positively correlated with larger absolute forecast errors. This is consistent with the hypothesized relationships between unexpected shocks and forecast errors. Absolute forecast errors are smaller after economic booms, measured as the economic growth above the previous 10-year median, with coefficients that are statistically significant for both the IMF and the Consensus/Focus Economics samples. This is consistent with the finding that forecasters have a harder time predicting recessions (Eicher et al., 2019). The level of development has no statistically significant bearing on the accuracy of forecasts. A persistent finding is that small countries (proxied by population size) have larger absolute growth forecast errors. However, this might reflect the tendency of small countries to be more open and thus vulnerable to shocks that cause volatility. When growth volatility is accounted for, the relationship between country size (population) and absolute forecast errors is no longer statistically significant (see Table 3 columns 4 through 6).

As previously established, the MENA region tends to have the largest forecast errors. In the base regressions (Table 3 columns 1 through 3), where several factors are accounted for, the coefficient of the MENA dummy is statistically insignificant, but of considerable magnitude with a coefficient of 0.906 for World Bank absolute growth forecast errors, and 1.032 for IMF absolute growth forecast errors. One possible interpretation could be that weak statistical capacity as well as the prevalence of internal conflict and exposure to commodity shocks explains the higher growth forecast errors for the MENA region relative to the world, and thus accounting for these factors results in the coefficient of the MENA dummy losing statistical significance. However, the large magnitude of the MENA dummy coefficients weakens this argument. Furthermore, when growth volatility is accounted for (see Table 3 columns 4 through 6), the coefficient of the MENA dummy is statistically significant, at least at the 10% level, although the magnitude is somewhat lower. The more plausible interpretation is that while several of the factors accounted for explain why MENA has higher forecast errors, they do not fully explain why the growth forecasts are inaccurate in the MENA region.

Table 4 replicates Table 3, with the forecast error as the outcome variable, to capture optimism or pessimism bias. Countries with better data ecosystems (SCI) tend to have less optimistic growth forecasts. This finding is statistically significant across international institutions' forecast errors (see Table 4, columns 1 and 2). The relationship between the SCI score and forecast errors holds even after considering growth volatility (columns 4 through 6).

The findings that better data ecosystems reduce the forecast error (forecast optimism) may have several plausible interpretations, one of which is that forecasters tend to be wildly optimistic when data is scarce, and better data ecosystems serve as a check.

Table 4. Determinants of GDP Growth Forecast Errors (Forecast Optimism or Pessimism)

Y = Forecast Errors (Forecast Growth minus Realized Growth)	**Base Model**			**With Growth Volatility**		
	WB-GEP (2010-2020)	**IMF-WEO (2010-2020)**	**Consensus/ Focus Economics (2015-2020)**	**WB-GEP (2010-2020)**	**IMF-WEO (2010-2020)**	**Consensus/ Focus Economics (2015-2020)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log of SCI (lagged)	-3.097***	-3.146***	-1.984	-2.273***	-2.331***	-1.772
	(1.167)	(1.073)	(1.885)	(0.693)	(0.669)	(1.796)
MENA Dummy	1.264**	1.566**	1.088	1.005***	1.310***	1.121
	(0.598)	(0.618)	(0.825)	(0.359)	(0.356)	(0.770)
Growth Volatility (lagged)				0.350**	0.347**	0.222*
				(0.155)	(0.134)	(0.112)
Log of GDP Per Capita (lagged)	0.278	0.240	-0.316	0.114	0.078	-0.386
	(0.179)	(0.178)	(0.425)	(0.120)	(0.123)	(0.390)
Export Commodity Price Shocks (T)	5.708	3.101	-5.812	5.179	2.578	-5.158
	(3.510)	(4.360)	(9.109)	(3.377)	(4.850)	(9.410)
Internal Conflicts Shocks Dummy (T)	0.189	0.067	0.099	-0.133	-0.251	-0.296
	(0.309)	(0.330)	(0.508)	(0.256)	(0.271)	(0.512)
Log of Total Population (lagged)	-0.135***	-0.143**	-0.164	-0.082	-0.091	-0.073
	(0.049)	(0.059)	(0.116)	(0.058)	(0.063)	(0.108)
Boom Dummy =1 if Above Median Growth (lagged)	-0.172	-0.493**	-0.562	-0.166	-0.488**	-0.463
	(0.206)	(0.192)	(0.347)	(0.212)	(0.188)	(0.320)
Constant	14.199***	15.771***	15.044*	10.134***	11.749***	12.587
	(3.821)	(3.639)	(8.866)	(2.390)	(2.461)	(7.698)
Number of observations	1,242	1,242	326	1,242	1,242	326
R2	0.387	0.367	0.492	0.429	0.409	0.499
Adjusted R2	0.378	0.359	0.472	0.421	0.400	0.478
Number of Countries	*126*	*126*	*56*	*126*	*126*	*56*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.

Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. Columns (1) and (4) samples refer to same-year World Bank GEP January Forecasts sample from 2010 to 2020, covering 126 countries. This common sample is used to define the columns (2) and (5) samples, for same-year IMF WEO January Forecasts from 2010 to 2020. Columns (3) and (6) samples refer to same-year Consensus January Forecasts and the MENA Region Focus Economics January Forecasts, from 2015 to 2020, covering 56 countries, and are not forced to be a common sample with WB-GEP and IMF-WEO. Log of SCI (lagged) is the one-year lagged log of Statistical Capacity Indicator. Growth Volatility (lagged) is the one-year lagged rolling 10-year standard deviation of realized growth rates. Log of GDP Per Capita (lagged) is the one-year lagged log of GDP per capita in constant 2010 US dollars. Export Commodity Price Shocks (T) is the same-year log change in export commodity prices, it captures the direction of the commodity price shocks. Internal Conflicts Shocks Dummy (T) is the same-year dummy variable for internal conflict country-year pairs – as defined using the UCDP-Prio Dataset. Log of Total Population (lagged) is the one-year lagged log of population and is considered a proxy for the country size. Boom Dummy if Above Median Growth (lagged) is a one-year lagged dummy variable for economic booms if growth is greater than or equal to the previous 10-year median growth. Note that the unforeseen shocks taken into account in this regression occurred during the same year of the forecast, after the GDP growth forecasts were published in January.

V. Extensions

V.1 On the Sub-Components of Data Capacity and Transparency

Certain elements of the data ecosystem may matter more for forecasting growth than others. To test this, the SCI index is deconstructed into three subcomponents: (i) directly related to GDP forecasting; (ii) indirectly related through the macroeconomic framework; and (iii) other elements of the data ecosystem including the periodicity of micro and macro indicators, which capture overall quality of the data ecosystem.[11, 12] Direct elements include the periodicity of GDP growth data, import and export price indices, the industrial production index, and the updating of base years for national accounts and the consumer price index. The indirect elements related to the macroeconomic framework comprise standards for external debt reporting, government finance accounting, updated balance of payments manual, and subscription to the IMF's Special Data Dissemination Standards (SDDS). Regression results show that of the three subcomponents, the "other elements" of the data ecosystem, are statistically significantly correlated with lower forecast errors and absolute forecast errors, while the direct and indirect elements are not (see Appendix Table A2). This finding implies that for countries to improve their forecasting accuracy, the whole data ecosystem needs to be upgraded, not just certain elements of it. A limitation of this finding is that there is far less variation in the direct element of the SCI indicator, which may explain the lack of statistical strength.

V.2 Forecast Errors between Different Forecasters

We investigate the role of forecasters in explaining forecast errors. The type of forecaster may influence the magnitude of forecast errors or the optimism of forecasts. To take this into account, the data is restructured with each unit of observation being a forecaster for a country and year. Dummy variables are created to account for the different categorizations of forecasters.

Forecasters are divided into three categories based on the *institution* sources. These include the IMF (WEO dataset), the World Bank (GEP dataset) and private forecasters (Consensus/Focus Economics datasets). January GDP growth forecasts are used for the analysis across all forecaster types. Private forecasts are obtained from two sources. Forecasts for the MENA region are obtained from Focus Economics, while the private forecasts from the rest of the world are source from the Consensus Economics dataset. Equations (1) and (2) are altered to include them as follows:

$$AbsFcstErr_{i,t,f} = \alpha + \beta_1\, LogSCI_{i,t-1} + \beta_2\, LogGDPpc_{i,t-1} + \beta_3\, Abs\Delta LogExpPrices_{i,t} + \beta_4\, InternalConflict_{i,t} + \beta_5\, LogPop_{i,t-1} + \beta_6\, Boom_{i,t-1} + \beta_7\, IMF\_Dummy_f + \beta_8 Consensus\_Dummy_f + \tau_t + \varepsilon_{i,t} \quad (3)$$

[11] Each indicator in the SCI is a score from 0 to 100. Each sub-component is calculated as the simple average of its indicator scores divided by 100, to adjust the scale from 0 to 1.

[12] For a cross-section of 145 countries over the period (2004-2020): (i) the correlation between the SCI and SCI GDP Direct sub-component is 0.72; (ii) the correlation between the SCI and SCI GDP Indirect sub-component is 0.78; and (iii) the correlation between the SCI and SCI Other Data Ecosystem (Other) sub-component is 0.93.

$$FcstErr_{i,t,f} = \alpha + \beta_1 \, LogSCI_{i,t-1} + \beta_2 \, LogGDPpc_{i,t-1} + \beta_3 \, \Delta LogExpPrices_{i,t} + \beta_4 \, InternalConflict_{i,t} + \beta_5 \, LogPop_{i,t-1} + \beta_6 \, Boom_{i,t-1} + \beta_7 \, IMF\_Dummy_f + \beta_8 ConsFocus\_Dummy_f + \tau_t + \varepsilon_{i,t} \quad (4)$$

where i is for country; t is for year; and f is for forecaster. A dummy is created for IMF forecasts (IMF_Dummy) and Consensus/Focus Economics-sourced forecasts ($ConsFocus\_Dummy$). World Bank forecasts are the comparison benchmark hence omitted in the model.

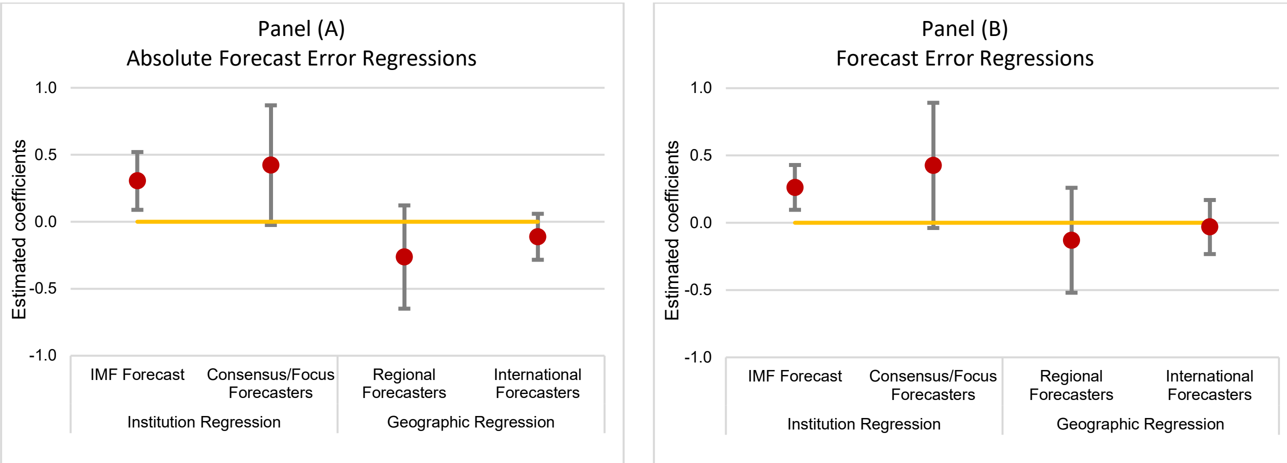
Alternatively, forecasters are divided into *geographic* sources. The geographical characterization distinguishes between international, regional, and local forecast types based on the proximity of the forecaster's headquarters to the country whose GDP is being forecasted. Local forecasters are those whose headquarters are in the same country of the GDP forecast. Regional forecasters are located in the same region but not in the country of the GDP forecast. International forecasters are those that are not in the region of the country whose GDP is being forecasted.

The relationship between forecast errors and forecaster type are presented in Appendix Tables A3 and A4. The coefficients from the regressions are plotted in Figure 3. The Institution Regression of Panel A compares the IMF and private sector's accuracy with the World Bank's (the omitted category). The Geographic Regression of Panel A compares the regional and international forecasters' accuracy with local forecasters (the omitted category). Panel B retains the same structure but provides the results for forecast optimism.

On average, IMF forecasts are more optimistic and less accurate than World Bank forecasts. Depending on the specification, IMF WEO's forecast are about 0.2 to 0.3 percentage points more optimistic than the World Bank GEP's forecasts. Consensus/Focus Economics forecasts are also more optimistic and less accurate than the IMF and World Bank forecasts. However, the Consensus/Focus Economics forecast coefficients are statistically insignificant, reflecting a large variation in the views of private-sector forecasters.

The accuracy and optimism of forecasts are largely similar across international, regional and local forecasters. Regional forecasts exhibit considerable variation in accuracy, although on average they do not differ from international and local forecasters. Local forecasters might have better access to local information that could improve their growth forecasts. But they might also be easily influenced by and connected to governments, which could influence their growth forecasts. The finding suggests that the two opposing effects could be offsetting each other.

Figure 3. GDP Growth Forecast Errors by Geographical and Institution Type



Source: Authors' calculations based on the January Consensus/Focus Economics Forecasts, the International Monetary Fund's January *World Economic Outlook* (WEO) and the World Bank's January *Global Economic Prospects* (GEP).
Note: This figure shows the results of two separate regressions for forecasters classified according to their institution type; and classified according to geography. In the institution regressions, the three categories are WB-GEP, IMF-WEO and Consensus/Focus Economics: WB-GEP is the omitted category. In the geographic regressions, the international, regional, and local categorization is based on the proximity of the forecaster's headquarters to the country being forecasted: "Local Forecasters" is the omitted category. Same-year forecasts in January are used for WB-GEP Forecasts (2010-2020), IMF-WEO Forecasts (2010-2020) and Consensus/Focus Economics Forecasts (2015-2020) for a pooled sample of 132 countries. Bars represent 90 percent confidence intervals. 16.6 percent of forecasts in the sample are by local forecasters. 17 percent of forecasts in the sample are by regional forecasters. 66.4 percent of forecasts in the sample are by international forecasters. There are a total of 218 local forecasters, 93 regional forecasters, and 107 international forecasters in the sample.

V.3 Short-term vs Long-term Forecast Errors

Thus far, the determinants of same-year GDP growth forecast errors have been investigated, but another question to be considered is how the impact of data capacity and transparency matter for longer-term forecasts. To do this, we examine the association between SCI and the World Bank GEP's one-year ahead GDP growth forecast error (e.g., 2020 growth forecasts are made in January 2019) and two-year ahead GDP growth forecast error (e.g., 2020 growth forecasts are made in January 2018).[13]

SCI remains statistically significant with the expected sign, for both one-year ahead forecast errors and absolute forecast errors, with and without growth volatility (See Appendix Table A5). This suggests that better data systems still allow forecasters to paint a more accurate and less biased picture of a more distant future. However, the importance of SCI in the accuracy of one-year ahead forecasts seems smaller than same-year forecasts, as the magnitude of SCI in Appendix Table A5 is smaller than that in Tables 3 and 4 (for example, -1.50 shown in column 2 of Appendix Table A5 versus -3.1 shown in column 1 of Table 4).

The association of SCI and two-year ahead forecast errors is also explored, but at a cost. Data of the World Bank GEP's two-year ahead GDP growth forecast errors only start in 2015. Despite this limited sample, there are points to be made. SCI remains statistically significant for the two-year ahead forecast errors and absolute forecast errors (Appendix Table A6). Similar to one-year ahead forecasts, the magnitude of

[13] GEP generally does not provide three-year ahead forecasts.

the coefficient of SCI is also smaller than that of the same-year forecast error, indicating a lesser importance of SCI in the accuracy of two-year ahead forecasts.

Logically, the more forecasts are projected in the future, the more they carry an element of uncertainty. Therefore, information in the time of forecasting may be rendered obsolete the longer the horizon of forecasts. In addition, the risk of more unforeseen events increases, as well as their unpredictable impacts. An example is forecasts for the year 2022. Looking at forecasts made in 2021 for 2022, the focus was on post-pandemic recovery, with no knowledge of a potential conflict that would impact all international markets.

VI. Robustness Checks

VI.1 Alternative Measure of Data Transparency: Statistical Performance Indicator

The estimations are replicated using an alternative index—the Statistical Performance Indicator (SPI) — which, as detailed above, is more comprehensive. For instance, the SPI includes availability and frequency of labor force surveys, establishment surveys, and establishment censuses that are not included in the SCI. The SPI also covers the periodicity and timeliness of the Sustainable Development Goals (SDGs) indicators as well as indicators of data openness that were not covered in the SCI. More importantly, the SPI is more global in nature, including both developing and developed economies, while the SCI largely includes developing economies. Yet the SPI is available for a shorter period (2016–2019) than the SCI (2004–2020). Appendix Table A7 presents the findings for the lagged log of SPI indicator with both a global sample and a largely developing economies sample. These samples are determined by the availability of IMF-WEO Global sample and World Bank GEP sample respectively. The findings largely mirror those with the SCI—improvements in data transparency are positively correlated with forecast accuracy (absolute forecast errors) and reduce forecast optimism (forecast errors). However, the findings for forecast optimism are statistically significant, while the findings for forecast accuracy are not. Global sample coefficients are greater than those for just developing economies, suggesting that the effects of good data systems are much stronger in a sample that compares the performance of data systems in both advanced and developing economies. The results indicate that the positive effects of good data ecosystems are robust to the choice of the data transparency indicator.

VI.2 Other Control Variables: Institutions, Polity, Informality, and Natural Disasters

This robustness check includes other potential factors that may affect forecast errors. They are institutions (proxied by rule of law), polity, informality, and natural disasters. The first three belong to the information set of forecasters at the time of forecasts at the beginning of the year (January), while natural disasters are considered as shocks that occurred during the year of the forecast.

The quality of political institutions may affect forecast errors. Merola and Pérez (2013) observe fiscal forecast over-optimism in election years not just in forecasts made by European governments but also, albeit to a lesser extent, in forecasts made for European countries by international organizations like the European Commission (EC) and the OECD. A system of checks and balances that restricts the power of the executive is a feature of a strong democracy (De Montesquieu, 1989). Therefore, we account for the quality of political institutions using the Polity Index and the Rule of Law Indicator. The Polity Index is defined as the lag of the combined polity score that is computed by subtracting the autocracy score from the democracy score, hence, the resulting unified polity scale ranges from +10 (strongly democratic) to -10 (strongly autocratic). The Rule of law Indicator is the lagged rule of law indicator which is one of the six Worldwide Governance Indicators. It captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

We also check the robustness of our results to the informal sector. Blanchard and Leigh (2013) find that errors in official forecasts of fiscal consolidation effects are prevalent across many countries. Such errors, according to Pappa et al. (2015), are caused by the absence of the informal sector in standard models. When taxes increase in these models, agents may opt to work and invest less. Agents do, however, have an alternative option in an economy with an informal sector, which is to shift their activities to the shadow economy. This makes it easier for more resources to leave the formal sector, which causes recorded output and tax income to decline sharply. A recession may turn out to be worse than forecasted, but it may also not be as bad as it seems because the resources that leave the formal sector are employed in the informal sector. As a result, the decline in true (formal plus informal) output can be much smaller than that in recorded output. Dellas et al. (2017) found that the standard modeling practice of overlooking the informal sector is largely responsible for the significant forecast errors associated with the fiscal consolidation in Greece during the Euro Area Debt Crisis. In this sense, informality can affect GDP growth forecast errors, and we account for it using self-employment as a proxy, which is defined as the lag of total self-employed as a percentage of the total employment based on modeled ILO estimates.

Our findings are robust to the inclusion of natural disasters. Unpredictable and costly occurrences like natural disasters can have a detrimental impact on many economies. Celasun et al. (2021) found that the IMF's WEO GDP growth forecasts have a tendency to be upwardly biased in part due to the rarity of unforeseen growth booms compared to significant growth collapses brought on by natural disasters, armed conflicts, and systemic financial crises. Loayza et al. (2012) investigated the effects of the different natural disasters (i.e., droughts, floods, earthquakes, and storms) separately by economic sector (agriculture, industry, and services) and found that natural disasters have a greater impact on growth in developing countries than in developed ones, with more industries being impacted and more significant economic repercussions. Depending on the type of disaster and the affected economic sectors, disasters can have positive or negative effects on economic growth. Severe disasters have no beneficial growth impact, even though moderate calamities (such as mild floods) can spur growth in some industries (Loayza et al., 2012). In a recent study, Kong et al. (2021) examined the changes in analyst optimism degree in earnings forecasts following earthquake events in China. They revealed that analysts utilize heuristics to forecast earnings and become irrationally pessimistic when an earthquake occurrence is salient. Analysts do, however, rectify the bias after the initial irrational predictions. Hence, we include in our analysis a natural disasters shocks dummy that is equal to 1 when severe natural disasters had occurred in a country. Severe natural disasters are those that generate damages equivalent to at least 1 percent of the GDP of the country affected that year (based on the total estimated damages reported by EM-DAT). Disasters include floods, earthquakes, droughts, storms, landslides, volcanic activities, extreme temperatures, and wildfires.

Appendix Table A8 shows that the relationship between SCI and forecast error remains robust, although the sample size shrinks. After accounting for the aforementioned additional factors, the quality of the data ecosystem seems to matter less for the forecast accuracy, as the magnitude of the SCI decreases and is less statistically significant across the World Bank, IMF, and private sector's samples (columns 1 through 3), given the smaller sample size. The coefficient of the MENA dummy is also statistically insignificant, possibly suggesting that MENA has high absolute forecast errors due to these additional factors. However, data capacity reduces the forecast optimism bias (forecast errors) and remains statistically significant at the 5 percent level for both the World Bank and the IMF's samples (columns 4 and 5). The coefficient of the MENA dummy is also statistically significant, and thus the findings are not definitive in explaining why the MENA region tends to have optimistic growth forecasts.

VI.3 Excluding Fragile, Conflict and Violence-affected (FCV) Countries

This robustness check shows that the relationship between data capacity and transparency and forecast errors holds even when FCV countries are excluded. Data capacity in FCV countries is typically severely weakened. Growth in these countries is also very difficult to forecast, because of the fragile and conflict nature. The association between data capacity and forecast errors is especially strong for FCV countries. They typically lie to the left of Figure 2.

Appendix Table A9 shows the result of the baseline regressions but dropping years of countries defined as FCV by the World Bank in those years.[14] The omission of the FCV countries from the baseline regressions undermines, but does not eliminate, the relationship between the data capacity and forecast accuracy. The SCI remains negatively associated with the absolute GDP growth forecast errors across World Bank, IMF, and private sector's samples. However, the magnitude of the SCI decreased considerably and is less statistically significant than in the baseline regression (columns 1 through 3). On the other hand, the finding that better data ecosystems lower forecast optimism bias remains robust even after the exclusion of FCV countries. SCI remains statistically significantly correlated (at 10 percent level) with forecast errors across the World Bank and IMF's samples (columns 4 and 5).

VII. Conclusions

Economic forecasts matter for government decisions. They are inputs to the formulation of policies that aim to safeguard and advance economies. Accurate forecasts enhance the possibility of timely and targeted interventions.

This paper examines the role of a country's data capacity in explaining GDP growth forecast errors. It reports four main sets of findings. First, same-year GDP growth forecast error—the difference between forecasted GDP growth and realized GDP growth— is large. Globally, between 2010 and 2020, the average same-year forecast error is 1.3 percentage points for the January World Bank forecasts and 1.5 percentage points for the January IMF forecasts. The Middle East and North Africa region (MENA) has the largest forecast errors among the world regions. Second, data capacity and transparency significantly explains forecast errors. On average, if a country's Statistical Capacity Index, a measure of data capacity and transparency, improves by 1 standard deviation, the average same-year absolute forecast error by the World Bank is lower by 0.44 percentage points. The results are robust to a battery of control variables and robustness checks. Third, the role of the overall data ecosystem, not just those elements related to growth forecasting, is important for the accuracy of GDP growth forecasts. Finally, GDP growth forecasts from the World Bank are more accurate and less optimistic than those from the IMF and the private sector.

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[14] The FCV countries are defined according to the World Bank's classification. "Fragile Situations" have either a harmonized average Country Policy and Institutional Assessment (CPIA) country rating of 3.2 or less, or the presence of a United Nations and/or regional peacekeeping or peace-building mission during the past three years. This list includes only IDA eligible countries and non-member or inactive territories/countries without CPIA data. IBRD countries with CPIA ratings below 3.2 do not qualify on those grounds, because of non-disclosure of IBRD countries' CPIA ratings. IBRD countries that are included qualify only by the presence of a peacekeeping, political or peace-building mission, and their CPIA ratings are thus not indicated here. The list of FCV countries is updated every fiscal year. Countries are flagged as FCV for a given year if they are on the updated FCV list for that year.

We emphasize that data capacity and transparency matter for a lot more than just the accuracy of GDP growth forecasts. Credible and timely data can serve policy actions. Data that are accessible to the broader research and civil society can generate better analyses which form the basis for discussions and reforms. Data transparency, in general, can build trust, hold governments accountable and improve institutional quality and growth (see Islam and Lederman, 2020).

We conclude by highlighting some practical recommendations that emerged from conversations with World Bank country economists on how to improve the quality of data to generate more accurate forecasts. Fundamentally, increasing the frequency and quality of national accounts data can improve forecasts considerably. It is also important that the underlying data is consistent within the country, and this can be achieved through better communication between ministries and national statistical offices. There is scope for technical assistance from international organizations to help governments improve the quality of national statistics, which in turn will improve the information that is fed into forecast models. Finally, accessing data for countries in conflict is quite challenging. These economies drive a lot of the inaccuracy in regional forecasts. However, there is some hope. For countries in conflict, alternative data sources such as information from satellites (for example, night lights data) are crucial and, in this regard, the international institutions can play an important role in facilitating access to such data.

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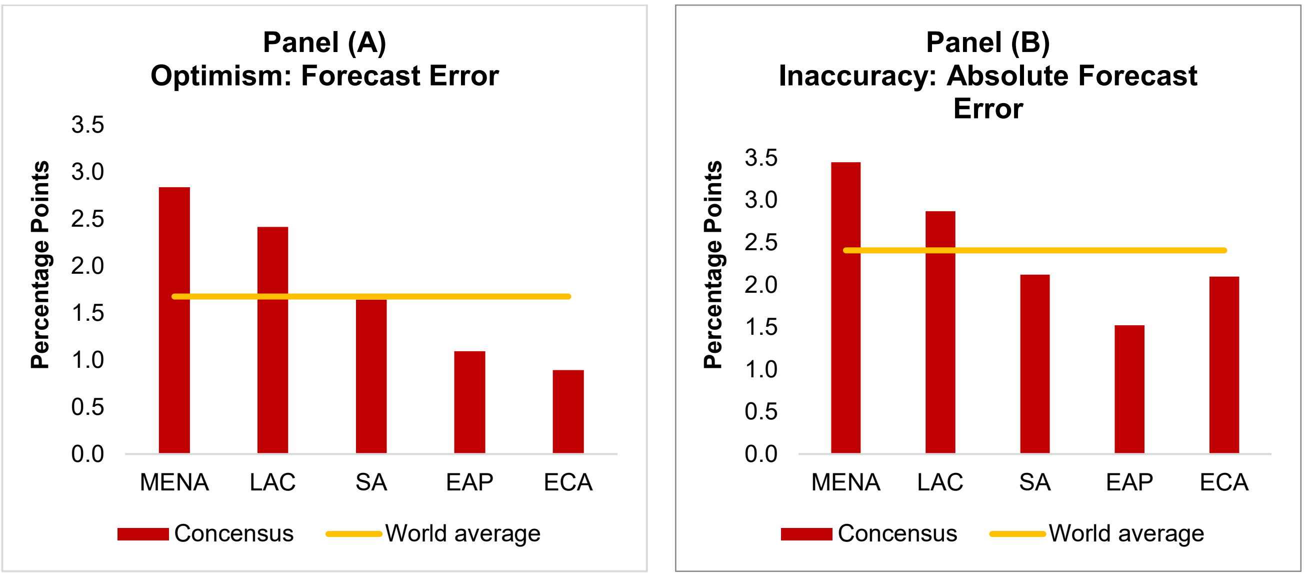
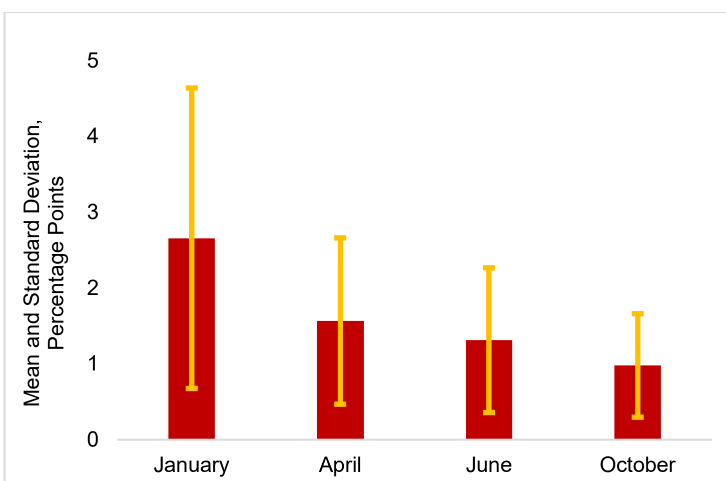
Appendix

Appendix Figure A1. January Same-Year GDP Growth Forecast Errors from Private Forecasters by Region (2015–2020)



Source: Authors' calculations based on the January Consensus/Focus Economics Forecasts.
Note: The figure displays the same-year January GDP growth forecast errors (Panel A) and absolute GDP growth forecast errors (Panel B) of Consensus/Focus Economics Forecasts that largely include private forecasters. Forecast errors are calculated as the forecasted GDP growth rates minus realized GDP growth rates. Absolute forecast errors are calculated as the absolute value of the forecast errors. The figure is constructed based on a sample of 80 countries (largely developing economies) collected in January for each year between 2015 and 2020. The MENA region includes both GCC and non-GCC countries.

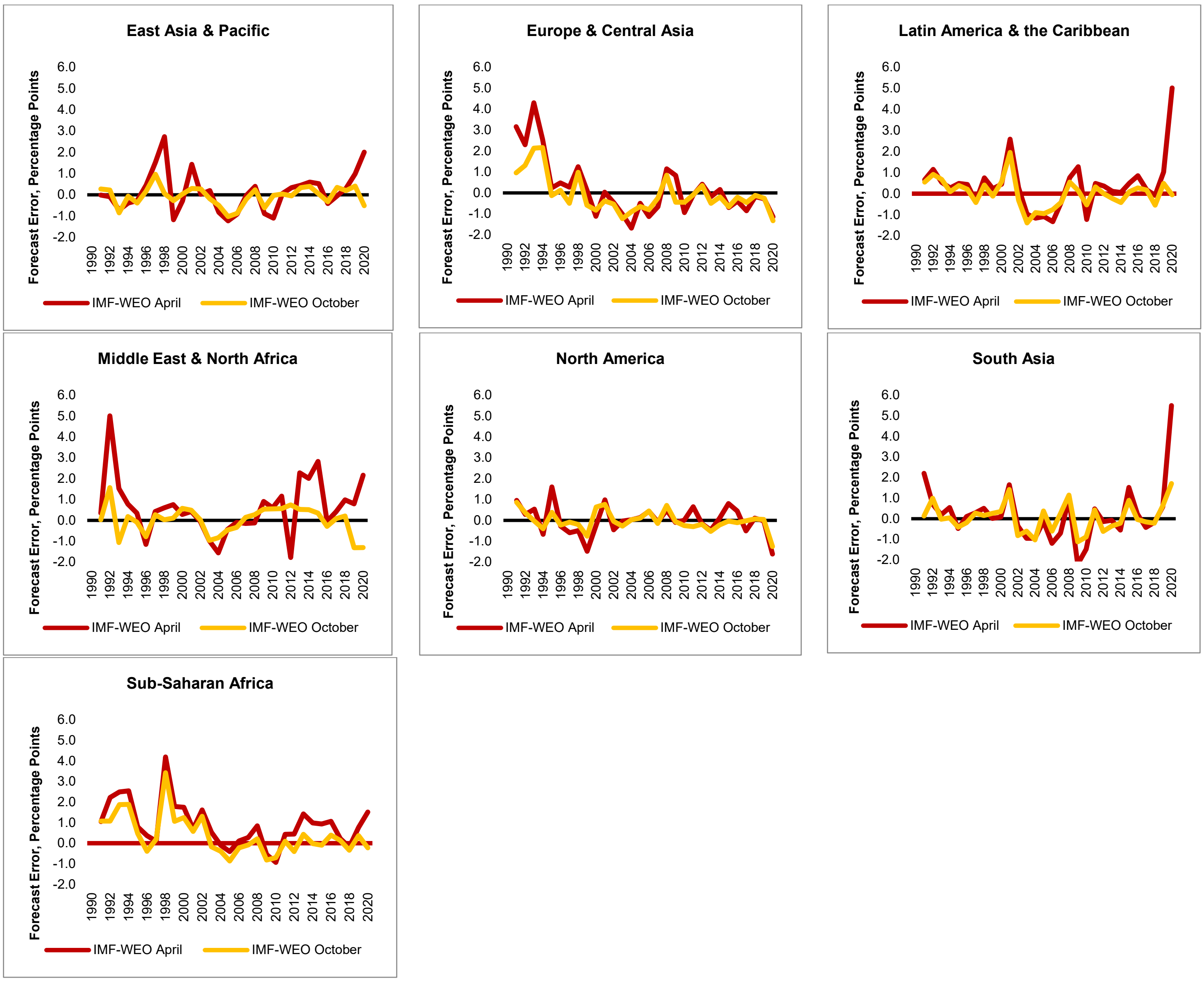
Appendix Figure A2. Same-Year Absolute GDP Growth Forecast Errors by Month



Source: Authors' calculations based on the International Monetary Fund's January, April, June, and October *World Economic Outlook*.

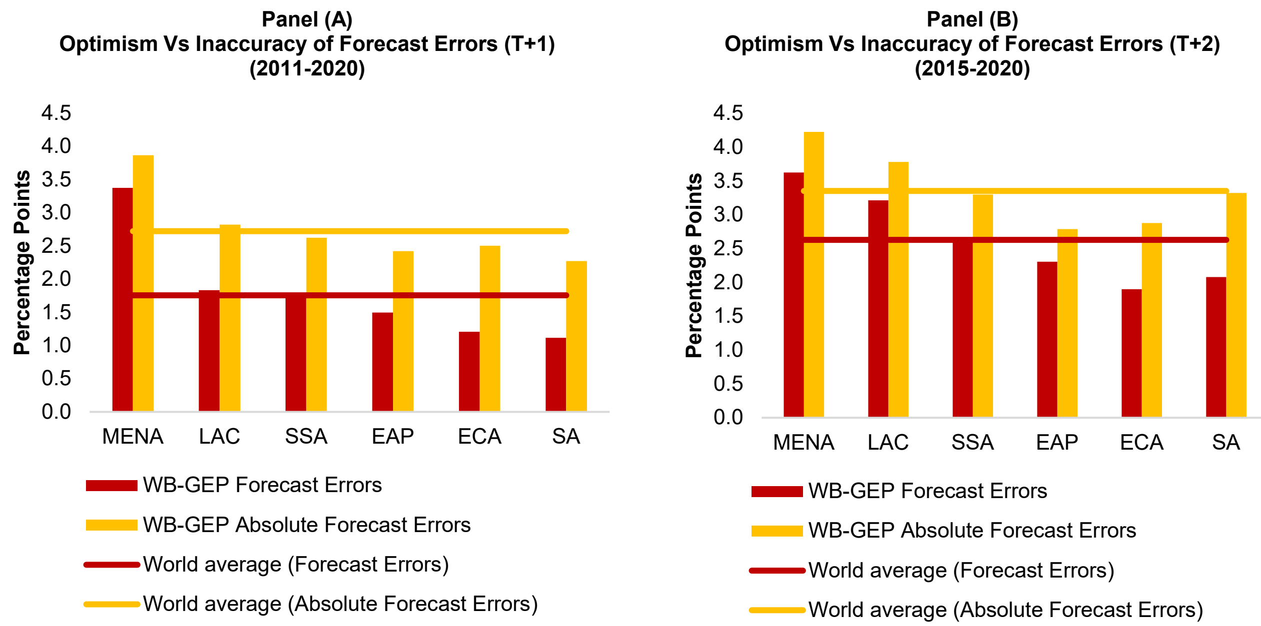
Note*:* This figure is produced based on same-year forecast errors from the January, April, June and October Forecasts, frossm 2010 to 2020. The 125-country sample is defined by the sample of the World Bank's January *Global Economic Prospects.* Upper (lower) bound is defined as half a standard deviation above (below) the mean.

Appendix Figure A3. Long Run Regional Same-Year GDP Growth Forecast Errors



Source: Authors' calculations based on the International Monetary Fund's April and October *World Economic Outlook.*
Note: The figure displays same-year April and October GDP growth forecast errors and same-year absolute GDP growth forecast errors of the IMF's *World Economic Outlook*. Forecast errors are calculated as the forecasted GDP growth rates minus realized GDP growth rates. Absolute forecast errors are calculated as the absolute value of the forecast errors. The figure is constructed based on a sample of 190 countries from 1990 to 2020. Note that the IMF's April and October *World Economic Outlook* data have longer coverage than the IMF's January *World Economic Outlook* and the World Bank's January *Global Economic Prospects*. The MENA region includes both GCC and non-GCC countries.

Appendix Figure A4. Short-term Vs Long-term GDP Growth Forecast Errors by Region



Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*.
Note: The figure displays the one-year ahead GDP growth forecast errors and absolute GDP growth forecast errors (Panel A) and the two-year ahead GDP growth forecast errors and absolute GDP growth forecast errors (Panel B) of the World Bank's *Global Economic Prospects* in January. Forecast errors are calculated as the forecasted GDP growth rates minus realized GDP growth rates. Absolute forecast errors are calculated as the absolute value of the forecast errors. Panel A is constructed based on a sample of 141 countries (largely developing economies) collected in January for one-year ahead forecasts between 2011 and 2020, while Panel B is constructed based on a sample of 135 countries (largely developing economies) collected in January for two-year ahead forecasts between 2015 and 2020. For example, the one-year ahead forecasts of January 2020 are collected from the January 2019 GEP report, while the two-year ahead forecasts of January 2020 are collected from the January 2018 GEP report. The MENA region includes both GCC and non-GCC countries. Controlling for the sample size of countries between T+1 and T+2 would result in a sample of 133 countries over the period (2015-2020) with higher forecast errors (2.4 percentage points) and absolute forecast errors (3.1 percentage points) in T+1, while in T+2 the results are roughly the same.

Appendix Table A1. Descriptive statistics (Imposing the Same Sample Size Across Different Forecast Horizons)

Variables	Number of countries	Number of observations	Mean	Standard Deviation	Median	Min	Max
WB-GEP Forecast Error (January) T	133	713	2.1	4.8	0.5	-7.9	63.5
WB-GEP Forecast Error (January) T+1	133	713	2.4	4.4	1.0	-12.4	33.2
WB-GEP Forecast Error (January) T+2	133	713	2.6	4.5	1.3	-19.5	28.7
WB-GEP Absolute Value of Forecast Error (January) T	133	713	2.8	4.4	1.3	0.0	63.5
WB-GEP Absolute Value of Forecast Error (January) T+1	133	713	3.1	4.0	1.6	0.0	33.2
WB-GEP Absolute Value of Forecast Error (January) T+2	133	713	3.3	4.0	1.8	0.0	28.7

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*.
Note: The table displays the summary statistics of GDP growth forecast errors and absolute GDP growth forecast errors of the World Bank's *Global Economic Prospects* in January for period T, T+1, and T+2. Forecast errors are calculated as the forecasted GDP growth rates minus realized GDP growth rates. Absolute forecast errors are calculated as the absolute value of the forecast errors. The table is constructed based on a common sample of 133 countries (largely developing economies) collected in January for period T, T+1, and T+2 between 2015 and 2020. For example, the same-year forecast errors for 2020, are calculated as the forecasted GDP growth for 2020, calculated in 2020, minus the actual 2020 GDP growth rate (which is published in 2021); the one-year ahead forecasts of January 2020 are collected from the January 2019 GEP report; and the two-year ahead forecasts of January 2020 are collected from the January 2018 GEP report.

Appendix Table A2. On the Role of SCI Sub-Indicators

	Base Model		With Growth Volatility	
Y = Outcome Variables	**Absolute Forecast Errors**	**Forecast Errors**	**Absolute Forecast Errors**	**Forecast Errors**
	WB-GEP (2010-2020)			
	(1)	**(2)**	**(3)**	**(4)**
Log of SCI: GDP Direct (lagged)	-0.368	-0.298	-0.447	-0.354
	(0.311)	(0.334)	(0.298)	(0.329)
Log of SCI: GDP Indirect (lagged)	-0.020	-0.249	-0.036	-0.240
	(0.338)	(0.305)	(0.241)	(0.291)
Log of SCI: Other Data Ecosystem Other (lagged)	-2.135*	-2.957**	-1.052*	-1.933***
	(1.181)	(1.193)	(0.632)	(0.726)
MENA Dummy	0.908	1.269**	0.632**	1.009***
	(0.666)	(0.594)	(0.298)	(0.363)
Growth Volatility (lagged)			0.392***	0.346**
			(0.142)	(0.156)
Log of GDP Per Capita (lagged)	0.258	0.238	0.139	0.112
	(0.191)	(0.182)	(0.118)	(0.134)
Export Commodity Price Shocks (T)		5.526		5.000
		(3.449)		(3.313)
Absolute Value of Export Commodity Price Shocks (T)	1.600		-1.719	
	(4.756)		(3.943)	
Internal Conflicts Shocks Dummy (T)	0.355	0.157	0.016	-0.156
	(0.287)	(0.303)	(0.202)	(0.255)
Log of Total Population (lagged)	-0.183***	-0.133***	-0.109**	-0.073
	(0.059)	(0.050)	(0.054)	(0.057)
Boom Dummy =1 if Above Median Growth (lagged)	-0.168	-0.161	-0.174	-0.160
	(0.185)	(0.210)	(0.198)	(0.215)
Constant	1.773	0.183	0.779	-0.518
	(2.412)	(2.287)	(1.791)	(1.959)
Number of observations	1,240	1,240	1,240	1,240
R2	0.347	0.389	0.415	0.431
Adjusted R2	0.337	0.380	0.406	0.421
Number of Countries	*126*	*126*	*126*	*126*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the World Bank's *Statistical Capacity Indicator*, the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.

Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. The same-year WB-GEP January Forecasts' sample of 126 countries between 2010-2020 is used for the forecast errors and absolute forecast errors.

Appendix Table A3. Pooled Regression: Forecaster type (Institutional)

	Base Model		**With Growth Volatility**	
Y = Outcome Variables	**Absolute Forecast Errors**	**Forecast Errors**	**Absolute Forecast Errors**	**Forecast Errors**
	(1)	**(3)**	**(2)**	**(4)**
Log of SCI (lagged)	-3.202**	-2.528**	-2.372***	-2.088**
	(1.481)	(1.064)	(0.835)	(0.891)
MENA Dummy	0.802	0.784	0.809	0.756
	(0.712)	(0.687)	(0.555)	(0.638)
Growth Volatility (lagged)			0.377***	0.163**
			(0.103)	(0.080)
Log of GDP Per Capita (lagged)	0.147	0.038	-0.046	-0.062
	(0.251)	(0.204)	(0.140)	(0.163)
Export Commodity Price Shocks (T)		-2.322		-2.698
		(5.128)		(5.261)
Absolute Value of Export Commodity Price Shocks (T)	7.626		2.723	
	(5.052)		(4.157)	
Internal Conflicts Shocks Dummy (T)	0.532*	0.008	0.278	-0.115
	(0.294)	(0.315)	(0.238)	(0.312)
Log of Total Population (lagged)	-0.172**	-0.130	-0.082	-0.092
	(0.084)	(0.080)	(0.076)	(0.075)
Boom Dummy =1 if Above Median Growth (lagged)	-0.318*	-0.359*	-0.290	-0.349*
	(0.189)	(0.191)	(0.181)	(0.180)
IMF Dummy	0.315**	0.275***	0.232***	0.240***
	(0.132)	(0.101)	(0.085)	(0.092)
Consensus/Focus Economics Dummy	0.302	0.311	0.228	0.287
	(0.245)	(0.245)	(0.210)	(0.221)
Constant	16.804***	13.614***	12.404***	11.426***
	(4.444)	(3.548)	(2.987)	(3.403)
Number of observations	8,334	8,334	8,334	8,334

R2	0.383	0.410	0.446	0.419
Adjusted R2	0.381	0.408	0.445	0.417
Number of Countries	*132*	*132*	*132*	*132*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.
Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. This table shows the results of regressions for forecasters classified according to their types: Institutional Regressions. The three categories are WB-GEP, IMF-WEO and Consensus/Focus Economics Forecasts: WB-GEP is the omitted category. Same-year forecasts in January are used for WB-GEP Forecasts (2010-2020), IMF-WEO Forecasts (2010-2020) and Consensus/Focus Economics Forecasts (2015-2020) for a pooled sample of 132 countries. The samples of GEP, WEO, and Consensus/Focus Economics are not forced to be a common sample.

Appendix Table A4. Pooled Regression: Forecaster type (Regional)

	Base Model		**With Growth Volatility**	
Y = Outcome Variables	**Absolute Forecast Errors**	**Forecast Errors**	**Absolute Forecast Errors**	**Forecast Errors**
	(1)	**(3)**	**(2)**	**(4)**
Log of SCI (lagged)	-3.185**	-2.481**	-2.313***	-2.017**
	(1.530)	(1.074)	(0.822)	(0.872)
MENA Dummy	0.835	0.821	0.814	0.781
	(0.708)	(0.696)	(0.556)	(0.652)
Growth Volatility (lagged)			0.380***	0.164**
			(0.102)	(0.081)
Log of GDP Per Capita (lagged)	0.174	0.071	-0.000	-0.020
	(0.224)	(0.184)	(0.125)	(0.153)
Export Commodity Price Shocks (T)		-2.360		-2.735
		(5.114)		(5.246)
Absolute Value of Export Commodity Price Shocks (T)	7.418		2.405	
	(5.070)		(4.180)	
Internal Conflicts Shocks Dummy (T)	0.555*	0.028	0.307	-0.094
	(0.282)	(0.309)	(0.230)	(0.305)
Log of Total Population (lagged)	-0.163**	-0.116	-0.071	-0.077
	(0.074)	(0.074)	(0.067)	(0.070)
Boom Dummy =1 if Above Median Growth (lagged)	-0.309	-0.352*	-0.272	-0.339*
	(0.190)	(0.193)	(0.181)	(0.182)
Regional Dummy	-0.265	-0.129	-0.286**	-0.134
	(0.231)	(0.234)	(0.127)	(0.224)
International Dummy	-0.161	-0.082	-0.019	-0.022
	(0.109)	(0.118)	(0.081)	(0.122)
Constant	16.742***	13.197***	11.820***	10.755***

	(4.784)	(3.357)	(2.609)	(2.948)
Number of observations	8,334	8,334	8,334	8,334
R2	0.383	0.409	0.447	0.418
Adjusted R2	0.381	0.408	0.445	0.417
Number of Countries	*132*	*132*	*132*	*132*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.
Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. Same-year forecasts in January are used for WB-GEP Forecasts (2010-2020), IMF-WEO Forecasts (2010-2020) and Consensus/Focus Economics Forecasts (2015-2020) for pooled a sample of 132 countries. The samples of GEP, WEO, and Consensus/Focus Economics are not forced to be a common sample. This table shows the results of a regression for forecasters classified according to geography. The international, regional, and local categorization is based on the proximity of the forecaster's headquarters to the country being forecasted: "local forecasters" is the omitted category. 16.6 percent of forecasts in the sample are by local forecasters. 17 percent of forecasts in the sample are by regional forecasters. 66.4 percent of forecasts in the sample are by international forecasters. There are a total of 218 local forecasters, 93 regional forecasters, and 107 international forecasters in the sample.

Appendix Table A5. Determinants of 1-Year Ahead GDP Growth Forecast Errors

	Base Model		**With Growth Volatility**	
Y = Outcome Variables	**Absolute Forecast Errors (T+1)**	**Forecast Errors (T+1)**	**Absolute Forecast Errors (T+1)**	**Forecast Errors (T+1)**
	WB-GEP (2011-2020)			
	(1)	**(2)**	**(3)**	**(4)**
Log of SCI (lagged)	-1.237*	-1.500**	-0.901**	-1.104**
	(0.651)	(0.640)	(0.443)	(0.517)
MENA Dummy	1.030	1.365**	0.977**	1.304***
	(0.644)	(0.541)	(0.469)	(0.443)
Growth Volatility (lagged)			0.350***	0.290***
			(0.084)	(0.097)
Log of GDP Per Capita (lagged)	0.222*	0.340**	0.113	0.227**
	(0.129)	(0.132)	(0.090)	(0.112)
Export Commodity Price Shocks (T+1)		3.318		5.448
		(3.493)		(3.677)
Absolute Value of Export Commodity Price Shocks (T+1)	3.641		-1.089	
	(3.496)		(3.417)	
Internal Conflicts Shocks Dummy (T+1)	0.336	0.373	0.072	0.141
	(0.274)	(0.312)	(0.242)	(0.290)
Log of Total Population (lagged)	-0.151**	-0.101*	-0.084	-0.050
	(0.059)	(0.060)	(0.054)	(0.061)
Boom Dummy =1 if Above Median Growth (lagged)	0.168	0.046	0.163	0.049
	(0.207)	(0.239)	(0.204)	(0.233)
Constant	8.022***	7.048***	5.452***	4.610**
	(2.510)	(2.188)	(1.742)	(1.818)
Number of observations	1,114	1,114	1,114	1,114
R2	0.406	0.405	0.461	0.434
Adjusted R2	0.398	0.397	0.453	0.425

Number of Countries	*125*	*125*	*125*	*125*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the World Bank's *Statistical Capacity Indicator*, the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.

Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. The WB-GEP *one-year ahead* January Forecasts 2011-2020 sample is used for forecast errors and absolute forecast errors, covering 125 countries. All variables indicated as "(lagged)" are two-year lagged variables from the forecasted year. For example, the information set of forecasters at the time of forecasting the one-year ahead GDP growth of 2020 (which is published in January 2019) would be based on the information available in 2018. Note that the unforeseen shocks taken into account in this regression occurred one-year later after the forecasts were published, for example, the one-year ahead GDP growth forecast of 2020 is published in 2019, and the shocks took place in the year 2020.

Appendix Table A6. Determinants of 2-Year Ahead GDP Growth Forecast Errors

	Base Model		**With Growth Volatility**	
Y = Outcome Variables	**Absolute Forecast Errors (T+2)**	**Forecast Errors (T+2)**	**Absolute Forecast Errors (T+2)**	**Forecast Errors (T+2)**
	WB-GEP (2015-2020)			
	(1)	**(2)**	**(3)**	**(4)**
Log of SCI (lagged)	-1.075	-1.334*	-1.051*	-1.189*
	(0.670)	(0.708)	(0.607)	(0.685)
MENA Dummy	0.853	0.721	0.897	0.737
	(0.714)	(0.593)	(0.643)	(0.566)
Growth Volatility (lagged)			0.203***	0.197***
			(0.057)	(0.075)
Log of GDP Per Capita (lagged)	0.362**	0.473**	0.332**	0.418**
	(0.158)	(0.204)	(0.146)	(0.192)
Export Commodity Price Shocks (T+2)		3.741		6.216
		(3.992)		(3.911)
Absolute Value of Export Commodity Price Shocks (T+2)	5.926		2.179	
	(4.376)		(3.946)	
Internal Conflicts Shocks Dummy (T+2)	0.089	0.119	-0.025	-0.010
	(0.319)	(0.356)	(0.301)	(0.345)
Log of Total Population (lagged)	-0.216***	-0.148	-0.169**	-0.107
	(0.078)	(0.100)	(0.079)	(0.102)
Boom Dummy =1 if Above Median Growth (lagged)	-0.174	-0.068	-0.168	-0.053
	(0.235)	(0.276)	(0.245)	(0.287)
Constant	7.414**	6.368*	6.278**	4.974
	(3.221)	(3.651)	(3.069)	(3.642)
Number of observations	681	681	681	681
R2	0.466	0.414	0.476	0.422
Adjusted R2	0.456	0.403	0.466	0.410
Number of Countries	*121*	*121*	*121*	*121*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the World Bank's *Statistical Capacity Indicator*, the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.
Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. The WB-GEP *two-year ahead* January Forecasts 2015-2020 sample is used for forecast errors and absolute forecast errors, covering 121 countries. All variables indicated as "(lagged)" are three-year lagged variables from the forecasted year. For example, the information set of forecasters at the time of forecasting the two-year ahead GDP growth of 2020 (which is published in January 2018) would be based on the information available in 2017.Note that the unforeseen shocks taken into account in this regression occurred two years later after the forecasts were published, for example, the two-year ahead GDP growth forecast of 2020 is published in 2018, and the shocks took place in the year 2020.

Appendix Table A7. SPI and GDP Growth Forecast Errors

	IMF-WEO (2016-2019)				WB-GEP (2016-2019)			
	Base Model		With Growth Volatility		Base Model		With Growth Volatility	
Y = Outcome Variables	Absolute Forecast Error	Forecast Error	Absolute Forecast Error	Forecast Error	Absolute Forecast Error	Forecast Error	Absolute Forecast Error	Forecast Error
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of SPI (lagged)	-3.267	-1.393*	-1.032	-2.037**	-0.895	-1.972*	-0.835	-1.950
	(2.459)	(0.761)	(0.882)	(1.003)	(1.156)	(1.133)	(1.179)	(1.180)
MENA Dummy	2.429**	1.315	1.488**	1.619*	0.203	0.380	0.247	0.378
	(1.129)	(0.909)	(0.611)	(0.845)	(0.573)	(0.594)	(0.547)	(0.590)
Growth Volatility (lagged)			0.599***	-0.147*			0.125	0.020
			(0.076)	(0.077)			(0.085)	(0.108)
Log of GDP per capita (lagged)	0.294	0.031	0.041	0.111	0.354*	0.491***	0.362*	0.488**
	(0.317)	(0.132)	(0.123)	(0.147)	(0.196)	(0.183)	(0.191)	(0.187)
Export Commodity Price Shocks		-3.903		-3.667		11.281*		11.286*
		(19.852)		(19.785)		(5.809)		(5.795)
Absolute value of Commodity Price Shocks	1.025		-8.480		-2.897		-4.996	
	(9.325)		(8.006)		(8.619)		(7.879)	
Internal Conflicts Shocks dummy	0.715	-0.323	-0.333	-0.054	0.064	0.121	0.027	0.114
	(0.811)	(0.519)	(0.356)	(0.405)	(0.291)	(0.343)	(0.294)	(0.353)
Log of Total Population (lagged)	-0.290***	-0.195**	-0.201**	-0.214**	-0.443***	-0.345***	-0.426***	-0.343***
	(0.101)	(0.098)	(0.085)	(0.101)	(0.087)	(0.098)	(0.090)	(0.101)
Boom Dummy =1 if Above Median Growth (lagged)	0.016	-0.398	-0.516*	-0.279	-0.223	-0.164	-0.221	-0.163
	(0.437)	(0.326)	(0.269)	(0.425)	(0.417)	(0.444)	(0.417)	(0.441)
Constant	23.825***	17.228***	14.170***	19.841***	9.410**	9.368**	8.481**	9.202**
	(6.987)	(3.066)	(3.406)	(3.449)	(3.636)	(3.694)	(3.992)	(4.077)
Number of observations	655	655	655	655	487	487	487	487
R2	0.399	0.402	0.544	0.410	0.486	0.526	0.487	0.526
Adjusted R2	0.390	0.393	0.537	0.400	0.475	0.516	0.476	0.515

Number of Countries	*165*	*165*	*165*	*165*	*124*	*124*	*124*	*124*

Source: Authors' calculations based on the International Monetary Fund's January *World Economic Outlook*, the World Bank's January *Global Economic Prospects*, the World Bank's *Statistical Performance Indicators,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.

Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2017. Columns (1) through (4) samples refer to the same-year IMF WEO January Forecasts sample from 2016 to 2019, covering 165 countries. Columns (5) through (8) samples refer to the same-year World Bank GEP January Forecasts sample from 2016 to 2019, covering 124 countries. The IMF WEO sample is a global sample, it comprises both developed and developing countries. Whereas the WB GEP sample mostly comprises developing economies plus the GCC countries. Both IMF WEO and WB GEP samples are determined by the availability of IMF WEO Forecasts data and WB GEP Forecasts data, respectively, as well as the regression covariates' data availability.

Appendix Table A8. Including Institutions, Polity, Informality and Natural Disasters

Y = Outcome Variables	Absolute Forecast Error (Base Model)			Forecast Error (Base Model)		
	WB-GEP (2010-2020)	IMF-WEO (2010-2020)	Consensus/ Focus Economics (2015-2020)	WB-GEP (2010-2020)	IMF-WEO (2010-2020)	Consensus/ Focus Economics (2015-2020)
	(1)	(2)	(3)	(4)	(5)	(6)
Log of SCI (lagged)	-0.393	-0.456	-0.096	-1.550***	-1.444**	-0.283
	(0.495)	(0.476)	(0.847)	(0.550)	(0.611)	(0.933)
MENA Dummy	0.508	0.716	0.701	1.049***	1.522***	0.901**
	(0.420)	(0.459)	(0.514)	(0.305)	(0.356)	(0.438)
Log of GDP Per Capita (lagged)	0.043	0.149	0.225	0.135	0.228	0.101
	(0.140)	(0.164)	(0.282)	(0.179)	(0.212)	(0.282)
Export Commodity Price Shocks (T)				4.120	-0.592	-2.528
				(4.218)	(4.559)	(3.559)
Absolute Value of Export Commodity Price Shocks (T)	6.734*	11.418***	5.652			
	(3.412)	(3.705)	(4.858)			
Internal Conflicts Shocks Dummy (T)	0.225	0.027	0.219	-0.006	-0.107	-0.074
	(0.227)	(0.256)	(0.276)	(0.228)	(0.253)	(0.319)
Log of Total Population (lagged)	-0.122**	-0.142**	-0.095	-0.046	-0.086	0.003
	(0.055)	(0.059)	(0.072)	(0.056)	(0.067)	(0.091)
Boom Dummy =1 if Above Median Growth (lagged)	-0.334**	-0.407***	-0.313	-0.360**	-0.661***	-0.245
	(0.134)	(0.142)	(0.194)	(0.181)	(0.181)	(0.301)
Rule of Law (lagged)	-0.468***	-0.575***	-0.346	-0.141	-0.368*	-0.136
	(0.169)	(0.181)	(0.224)	(0.171)	(0.217)	(0.178)
Polity (lagged)	0.021	0.025	-0.005	0.015	0.036*	0.032
	(0.020)	(0.022)	(0.023)	(0.019)	(0.021)	(0.023)
Informality (lagged)	0.003	0.009	-0.002	0.010	0.016	0.006
	(0.006)	(0.007)	(0.010)	(0.008)	(0.010)	(0.011)
Natural Disasters Shocks Dummy (T)	0.034	-0.136	0.108	0.313	0.241	0.801**
	(0.287)	(0.267)	(0.246)	(0.318)	(0.403)	(0.378)
Constant	4.487*	4.380*	1.146	6.758***	6.618**	0.460
	(2.559)	(2.626)	(5.088)	(2.559)	(2.772)	(4.800)
Number of observations	1,044	1,044	263	1,044	1,044	263
R2	0.065	0.080	0.134	0.100	0.143	0.095
Adjusted R2	0.047	0.062	0.082	0.082	0.126	0.040
Number of Countries	*116*	*116*	*54*	*116*	*116*	*54*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), the UCDP-PRIO Dataset for Conflict, the World Bank's *Worldwide Governance Indicators,* Polity5 dataset version 2018 from the Center for Systemic Peace, and the EM-DAT (The International Disaster Database).

Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. Columns (1) and (4) samples refer to same-year World Bank GEP January Forecasts sample from 2010 to 2020, covering 116 countries. This common sample is used to define the Columns (2) and (5) samples, for same-year IMF WEO January Forecasts from 2010 to 2020. Columns (3) and (6) samples refer to same-year Consensus January Forecasts and the MENA Region Focus Economics January Forecasts, from 2015 to 2020, covering 54 countries, and are not forced to be a common sample with WB-GEP and IMF-WEO. Note that the sample covers 68 severe natural disasters that occurred between 2010 and 2020 in 44 developing economies.

Appendix Table A9. Excluding FCV Countries-Years

Y = Outcome Variables	Absolute Forecast Error (Base Model)			Forecast Error (Base Model)		
	WB-GEP (2010-2020)	**IMF-WEO (2010-2020)**	**Consensus/Focus Economics (2015-2020)**	**WB-GEP (2010-2020)**	**IMF-WEO (2010-2020)**	**Consensus/ Focus Economics (2015-2020)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log of SCI (lagged)	-0.463	-0.639	-0.275	-1.414*	-1.244*	0.083
	(0.674)	(0.586)	(0.643)	(0.782)	(0.667)	(0.966)
MENA Dummy	-0.160	-0.103	0.024	0.442*	0.485*	-0.064
	(0.335)	(0.419)	(0.494)	(0.252)	(0.287)	(0.449)
Log of GDP Per Capita (lagged)	0.152	0.209**	0.135	0.152	0.163	-0.063
	(0.100)	(0.101)	(0.178)	(0.128)	(0.132)	(0.226)
Export Commodity Price Shocks (T)				2.663	1.074	1.897
				(4.353)	(4.243)	(6.401)
Absolute Value of Export Commodity Price Shocks (T)	2.468	3.058	-1.233			
	(3.534)	(3.817)	(3.355)			
Internal Conflicts Shocks Dummy (T)	0.274	0.280	0.383	0.157	0.225	0.016
	(0.167)	(0.216)	(0.280)	(0.254)	(0.296)	(0.413)
Log of Total Population (lagged)	-0.242***	-0.214***	-0.172*	-0.190***	-0.192***	-0.094
	(0.050)	(0.059)	(0.089)	(0.048)	(0.056)	(0.097)
Boom Dummy =1 if Above Median Growth (lagged)	-0.216	-0.438**	-0.573**	-0.286	-0.673***	-0.496
	(0.203)	(0.180)	(0.215)	(0.239)	(0.220)	(0.326)
Constant	6.298**	6.600***	4.332*	8.850***	8.870***	2.583
	(2.543)	(2.214)	(2.555)	(2.906)	(2.480)	(4.050)
Number of observations	1,014	1,014	305	1,014	1,014	305
R2	0.436	0.428	0.617	0.467	0.463	0.612
Adjusted R2	0.427	0.418	0.602	0.458	0.454	0.597
Number of Countries	*109*	*109*	*53*	*109*	*109*	*53*

Source: Authors' calculations based on the World Bank's January *Global Economic Prospects*, the International Monetary Fund's January *World Economic Outlook*, January Consensus Forecasts, January Focus Economics Forecasts, the World Bank's *Statistical Capacity Indicator,* the World Bank's *World Development Indicators*, the Export Commodity Price Shocks data from Gruss and Kebhaji (2019), and the UCDP-PRIO Dataset for Conflict.
Note: Statistical significance level 0.01 - ***; 0.05 - **; 0.1 - *. Regressions exclude all country-year pairs in fragile, conflict and violence-affected situations (FCVs) defined according to the World Bank's classification. Robust standard errors clustered at the country level. All regressions include year fixed effects, and the reference year is 2015. Columns (1) and (4) samples refer to same-year World Bank GEP January Forecasts sample from 2010 to 2020, covering 109 countries. This common sample is used to define the Columns (2) and (5) samples, for same-year IMF WEO January Forecasts from 2010 to 2020. Columns (3) and (6) samples refer to same-year Consensus January Forecasts and the MENA Region Focus Economics January Forecasts, from 2015 to 2020, covering 53 countries, and are not forced to be a common sample with WB-GEP and IMF-WEO.