The Predictability of Stock Market Volatility in Emerging Economies: Relative Roles of Local, Regional and Global Business Cycles*

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Abstract

This paper explores the role of business cycle proxies, measured by the output gap at the global, regional and local levels, as potential predictors of stock market volatility in the emerging BRICS nations. We observe that the emerging BRICS nations display a rather heterogeneous pattern when it comes to the relative role of idiosyncratic factors as a predictor of stock market volatility. While domestic output gap is found to capture significant predictive information for India and China particularly, the business cycles associated with emerging economies and the world in general are strongly important for the BRIC countries and weakly for South Africa, especially in the post-global financial crisis era. The findings suggest that despite the increase in the financial integration of world capital markets, emerging economies can still bear significant exposures to idiosyncratic risk factors, an issue of high importance for the profitability of global diversification strategies.

JEL Classification: C22, C53, E32, G10

Keywords: Stock Market Volatility, Business Cycles, BRICS, Forecasting

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1 Introduction

Return volatility is a key component of asset valuation, hedging as well as portfolio optimization models. Inaccurate forecasts of volatility may lead to mis-pricing in financial markets, over/under-hedged business risks and incorrect capital budgeting decisions, with significant implications on earnings and cash flows. To that end, monitoring and modeling stock market volatility is crucial not only for investors and corporate decision makers, but also for policy makers in their assessment of financial fundamentals and investor sentiment. In one of the pioneering studies, building on the stock pricing models of Shiller (1981a,b) implying that stock market volatility is driven by the uncertainty factors that relate to the volatility of cash flows and the discount factor, Schwert (1981) suggests that business cycle fluctuations affect both future cash flow projections and the discount factor, and hence, stock market volatility. This argument has been recently empirically supported for the United States (US) and other developed stock markets (Canada, Japan and the United Kingdom (UK)) by Choudhry et al. (2016) and Demirer et al. (2019) based on tests of causality. In the case of emerging markets, however, several recent studies including Nier et al. (2014) and Miranda-Agrippino and Rey (2019) argue the presence of a global financial cycle to drive asset prices in global markets, partially driven by the monetary policy decisions by the U.S. Fed (Bruno and Shin, 2018; Passari and Rey, 2015; Rey, 2018), while Anaya et al. (2017) argues that the U.S Fed monetary policy serves as a significant driver of financial and economic conditions in emerging economies.

Given the emerging evidence in the literature that a global financial cycle serves as a significant driver of price fluctuations in emerging financial markets, this paper adopts a broader approach and explores the predictive power of domestic, regional and global business cycles on the (realized) volatility of emerging stock markets, with a focus on the major emerging nations in the BRICS group, i.e. Brazil, Russia, India, China, and South Africa. To do so, we build on the recent evidence by Atanasov (2018) that world output gap serves as a global business cycle indicator, capturing significant predictive information for aggregate stock market returns, both in-sample and out-of-sample. Extending this line of reasoning to the global, regional and local contexts, we explore the relative roles of local and global business cycle proxies as potential predictors of stock market volatility in emerging nations. We then compare our results with those for the US, given its importance in the global financial system as well as the evidence of a significant U.S. monetary policy effect on emerging financial market valuations (Anaya et al., 2017). Finally, considering that the ultimate test of any predictive model (in terms of econometric frameworks and predictors) is in its out-of-sample performance (Campbell, 2008), we conduct a full-fledged forecasting exercise. By doing so, this paper extends the emerging literature on the effect of a global financial cycle on emerging economies and the role of output gap as a business cycle proxy in the context of stock market volatility forecasting.

The empirical basis to relate the output gap to stock market volatility is well established in the literature. In an earlier study, Cooper and Priestley (2009) argue that the output gap is a prime business cycle indicator by showing that output gap has a positive relationship with a number of highly procyclical variables including the growth rates in aggregate corporate earnings, real GDP, industrial production and a negative relationship with the term structure of interest rates. At the same time, a well-established strand of the literature provides ample evidence linking stock market volatility to real economic activity (e.g., Hamilton and Lin, 1996; Schwert, 2011), establishing a strong link between stock market volatility and macroeconomic fundamentals (see Engle and Rangel, 2008; Diebold and Yilmaz, 2008; Corradi et al., 2013). More recently, Atanasov (2018) shows that the predictive power of world output gap over excess stock returns stems from both the cash-flow and discount-rate channels, suggesting that the time variation in expected stock returns is driven by the market's response to changing business conditions and reflects time-varying risk or risk aversion.

Considering rational asset pricing models that formulate asset prices as a function of expected cash flows discounted at a rate that reflects inherent investment risks, the predictive power of output gap over stock market volatility can be due to the (i) cash-flow channel as the time variation in output gap as an indicator of real economic activity drives uncertainty in expected cash flows; and/or (ii) discount rate channel as output gap captures information regarding time-varying risk or risk aversion in the marketplace. Finally, given the evidence in Atanasov (2018) of strong predictive power of the output gap over excess stock returns, a third channel that links the output gap to stock market volatility can be due to the so-called "leverage effect" which refers to the empirical evidence that establishes a link between asset returns and volatility (e.g., Christie, 1982).

Our empirical analysis of emerging markets focuses specifically on the BRICS nations, given the emergence of this bloc as a powerful economic force, already contributing to more than a quarter of global output, which in turn, is expected to surpass that of the G7 countries by 2050 (Naik et al., 2018; Plakandaras et al., 2019). In addition, trade by these economies with the rest of the world has been growing at a fast rate, with the strong economic performance of these countries linked to the high level of foreign direct investment in the private sector (Mensi et al., 2014; Ruzima and Boachie, 2018). Naturally, volatility in these key emerging stock markets is likely to contribute to uncertainty in global equity markets through the trade channel (Balli et al., 2019), and hence, accurate prediction of financial market volatility in this bloc is of high importance considering the growth trends mentioned above.

To the best of our knowledge, while the role of local and global business cycles have been emphasized for stock returns of the BRICS (Nitschka, 2014; Sousa et al., 2016),[1] this is the first paper to relate stock market volatility of these countries to business cycles.[2] We observe that the emerging BRICS nations display a rather heterogeneous pattern when it comes to the relative role of idiosyncratic factors as a predictor of stock market volatility. Our results show that while domestic output gap captures significant predictive information, particularly for India, Brazil and China, the business cycle proxies associated with emerging and world economies are important for all the members of the BRICS bloc barring South Africa, particularly in the

[1]For a detailed review of the impact of business cycles on stock returns of advanced economies primarily, see Atanasov (2018).

[2]Note that, as additional analysis, we also forecasted stock returns using our various measures of business cycles augmented in a benchmark model with dividend yield, short-term interest rate and inflation rate as controls. In general, our results are in line with Sousa et al. (2016), showing important predictive role for global measures of output gaps rather than domestic versions of the same. These results have been suppressed to save space as the focus of the paper is volatility, however, complete details are available upon request from the authors.

post global financial crisis period. The findings overall suggest that economic agents looking to invest in the BRICS equity markets can utilize regional and global business cycle proxies to improve the predictive accuracy of stock market volatility models, while emerging economies can still bear significant exposures to idiosyncratic risk factors despite the increase in the financial integration of world capital markets.

The remainder of the paper is organized as follows: Section 2 describes the data, Section 3 presents the econometric model and the results, while Section 4 presents the robustness checks. Finally, Section 5 concludes the paper.

2 Data description

As mentioned earlier, we focus our attention on five major emerging economies – Brazil, Russia, India, China, and South Africa – comprising as the BRICS bloc. The sample period ends in July 2018, but starts at different months in 1990s for the six countries. Specifically, based on data availability, the sample period begins in August 1994 for Brazil, February 1998 for Russia, June 1994 for China, and February 1990 for India and South Africa. The data set includes monthly metrics of overall realized volatility, its good and bad components (i.e. good/bad volatility), and various (domestic, regional and global) output gap measures as business cycle proxies as per Atanasov (2018).

Using daily MSCI stock market index data for the BRICS in US dollars, we compute the monthly realized volatility (RV) as the sum of squared log-returns (SR) over a specific month (Andersen and Bollerslev, 1998). Similarly, we compute good and bad volatility (RV) values on a monthly basis, however, based on only positive and negative log-returns respectively. The daily stock market data is derived from the Datastream database maintained by Thomson Reuters.

The output gap measure is computed in a similar fashion as in Atanasov (2018). However, as our goal is to examine the relative roles of local as well as regional and global proxies for output gap as predictors of realized stock market volatility, we construct output gap measures using domestic industrial production data for each country and five measures of regional or global industrial production (i.e. world excluding US, advanced economies excluding US, emerging markets, US, and OECD plus six major non-OECD countries, i.e. Brazil, China, India, Indonesia, Russia, and South Africa) by removing a quadratic time trend from the natural log of each industrial production measure. More specifically, we regress the natural log of each industrial production measure against a time trend t and its squared term t^2:

$$\log(IP_{it}) = \alpha_i + \beta_i \cdot t + \gamma_i \cdot t^2 + \epsilon_{it}, \tag{1}$$

where i = (DOM, WLDexUS, ADVexUS, EM, US, WLD), representing domestic, world excluding US, advanced economies excluding US, emerging markets, US, and OECD plus six major non-member countries, respectively. The output gap is defined as the fitted value of the error term ϵ_{it}. This yields six measures of output gap, denoted OG_DOM, OG_WLDexUS, OG_ADVexUS, OG_EM, OG_US, and OG_WLD, that are subsequently tested as potential predictors of stock market volatility. The domestic measures of industrial production for each of the six countries is derived from the IHS Global Insight database, while the corresponding regional values are obtained from the Database of Global Economic Indicators, maintained by the Federal Reserve Bank of Dallas.[3] Finally, the world output is based on the work of Baumeister and Hamilton (2019).[4] Table A1 in the Appendix presents descriptive statistics, including the sample averages, standard deviations, minima, maxima, and first-order autocorrelation coefficients.

[3] The data is available from: `https://www.dallasfed.org/institute/dgei`, which also contains further details on the construction of the alternative measures of industrial production.

[4] The data can be downloaded from the website of Professor Christiane Baumeister at: `https://sites.google.com/site/cjsbaumeister/research`.

3 Forecasting realized volatility with output gap measures

To forecast the realized volatility, we utilize the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) of Corsi (2009). The HAR-RV model has been shown to be quite successful in capturing important features, e.g. long memory, fat tails, and self-similarity, of volatility in financial market returns. We consider the HAR-RV model with the quarterly and yearly averages of monthly realized volatilities, i.e.,

$$RV_{t+h} = \alpha + \beta_m RV_t + \beta_q RVQA_t + \beta_y RVYA_t + \gamma OG_t + \epsilon_{t+h}, \text{ for } t = 12, ..., T_0 - h, \tag{2}$$

where the quarterly and yearly averages of monthly realized volatilities are defined as

$$RVQA_t = \frac{1}{3}\sum_{p=0}^{2} RV_{t-p}, \tag{3}$$

$$RVYA_t = \frac{1}{12}\sum_{p=0}^{11} RV_{t-p}. \tag{4}$$

We refer to Equation (2) as the augmented model and set the coefficient of output gap, γ, to zero in the benchmark model as a comparison. As mentioned earlier, our primary focus is to examine whether business cycle proxies at the local, regional and global levels predict realized volatilities. We also extract the first principal component from various measures of output gap and use this factor in place of the local, regional, or global output gap as the predictor in our specification.

We split the entire sample with T observations into two subsamples, one with the first T_0 observations for estimation and the other for forecast evaluation. Conditional on available information at time T_0, we construct the output gap measure by removing a quadratic trend from the natural log of industrial output, as shown in Equation (1), and then estimate the coefficients in the forecasting model (2) to generate the h-month ahead forecast of realized volatility as

$$\widehat{RV}_{T_0+h} = \widehat{\alpha} + \widehat{\beta}_m RV_{T_0} + \widehat{\beta}_q RVQA_{T_0} + \widehat{\beta}_y RVYA_{T_0}. \tag{5}$$

We use the recursive sampling method by adding one observation to the estimation sample at a time and re-estimating both the output gap and the coefficients in the forecasting model. We generate a sequence of out-of-sample RV forecasts and assess the out-of-sample predictability using the mean squared error (MSE), i.e.,

$$MSE(h) = \frac{1}{T - T_0 - h + 1} \sum_{t=T_0}^{T-h} \left(\widehat{RV}_{t+h} - RV_{t+h} \right)^2, \tag{6}$$

for both the augmented model and the benchmark model.

To evaluate the out-of-sample performance of the augmented model relative to the benchmark model, we utilize the out-of-sample R^2_{OS} statistic of Campbell and Thompson (2008) computed as

$$R^2_{OS}(h) = 1 - \frac{MSE(h)_{augmented}}{MSE(h)_{benchmark}}. \tag{7}$$

The R^2_{OS} statistic captures the proportional reduction in the MSE of the augmented model relative to the benchmark model. A positive value indicates that the augmented forecasting model outperforms the benchmark model in terms of the out-of-sample MSE.[5]

Three different forecast evaluation samples are considered: 2005M1-2018M7, 2010M1-2018M7, and 2015M1-2018M7. The first evaluation sample includes the global financial crisis of 2007-2008, the second spans over the post-crisis period, and the third covers the most recent four years only. Tables 1 to 3 report the findings for the out-of-sample forecasts for 1-, 3- and 12-month ahead forecast horizons. Across the three forecast horizons and three out-of-samples considered, we tend to observe strong predictive role of the domestic output gap for India par-

[5]The significance of the positive R^2_{OS} statistic reported in the tables is based on a one-side t-statistic, with the null hypothesis: $MSE(h)_{augmented} = MSE(h)_{benchmark}$, and alternate hypothesis: $MSE(h)_{augmented} < MSE(h)_{benchmark}$.

ticularly, and Brazil and China to some lesser degree at the one-year-ahead horizon. This is in contrast with the finding by Atanasov (2018) that world output gap captures a larger fraction of return variation than the national output gap in a sample of sixteen developed countries, highlighting the role of idiosyncratic factors in the case of emerging nations.

Given that China and India are the two largest emerging economies growing at relatively higher rates compared to the other three countries in the bloc, the dominant predictive role of domestic output gap over stock market volatility for these nations is perhaps not unexpected. In the case of Brazil, however, Roubini (2009) notes that economic growth in China may be of more significance to Brazil than that of the overall global economy. This argument is further supported recently by the evidence in Balcilar et al. (2018) of volatility spillover effects of geopolitical risks in the Brazilian stock market via channels of export trades and foreign direct investments from China. Nevertheless, despite the increase in the financial integration of world capital markets, it is interesting to observe that the largest economies in the BRICS group are still exposed to significant idiosyncratic risk factors, driving volatility in their stock markets. In most cases, the domestic output gap has the highest loading on the first principal component of various output gap measures, and hence using the first principal component as the predictor yields similar results.

Further examining the findings in the tables, we observe that output gap measures for the emerging markets and the world are also consistently important for Brazil, Russia, India and China, with the exception of South Africa. In general, the gains in accurately predicting volatility from these measures of output gaps are more concentrated in the post-crisis periods. This is understandable, given that the world economy was in deep recession on a prolonged basis during the global financial crisis, and hence, much information could not be deduced from business cycle proxies, either due to unusual market conditions or the state of investor sentiment. Interestingly, the role of the US output gap and the output gap of advanced economies excluding the US, and to a lesser extent, the output of world excluding the US, is rather weak and limited to Russia only, probably due to its role as a major oil exporter. This is in contrast with the common perception of the importance of US business cycles as a driver of global equity market movements, further suggesting that idiosyncratic factors may still be at play in the case of emerging economies, despite the increase in the financial integration of global economies.[6]

Finally, as shown in Tables A2 to A7 in the Appendix, we observe that output gap measures, once again primarily of the emerging and world economies, have stronger predictive power over good realized volatility than its bad counterpart for the BRICS group. This suggests that business cycle movements are associated more closely with the underlying positive returns rather than negative returns that are used to compute realized volatilities. From this result, one can be argue that commonality in emerging market business cycles are particularly strong during economic recoveries than slowdowns, perhaps due to heterogeneities in the way each emerging economy reacts to bad news. Interestingly, however, at the one-year-ahead horizon, predictability of good realized volatility is observed for South Africa originating from the business cycles of the emerging countries, perhaps due to volatility spillover effects from major emerging economies.

4 Robustness checks

As a robustness check, we consider two alternative detrending methods proposed by Hodrick and Prescott (1997) (HP) and Hamilton (2018) for the construction of output gap measures. We use the one-sided version of the HP filter to make sure that the information we use to compute the forecasts is available at time t. Hamilton (2018) shows that a regression of the variable at date t on the four most recent values as of date $t - h$ achieves all the objectives sought by users of the Hodrick and Prescott (1997) filter with none of its drawbacks.[7] For monthly da-

[6] In a recent paper, Bouri et al. (2018) highlight the importance of domestic factors in explaining the stock market volatility in BRICS countries in addition to global risk factors. In this regard, the authors also point to the importance of crude oil for Russia and gold and crude oil for South Africa.

[7] Hamilton (2018) shows that the HP filter produces series with spurious dynamic relations that have no basis in the underlying data-generating process and suffers from an end-of-sample bias. The residuals from a regression of the variable at date t on the four most recent values as of date $t - h$ provide a better alternative to estimating the cyclical component. This one-sided filter does not rely on any assumptions as required by the HP filter and it preserves the underlying dynamic relations of the data.

ta, the author suggests using $h = 24$. Following this, we replicate the analysis in Section 3 by applying the one-sided HP and the Hamilton (2018) filters to the natural log of industrial production instead of removing a quadratic time trend.

When the one-sided HP filter is used, output gap does not improve the forecasting accuracy of the model in general, except for China where the forecasting error is slightly reduced; see Tables A8 to A10. This result is not unexpected given the strong concerns about the HP filter raised by Hamilton (2018). The results associated with the Hamilton (2018) filter presented in Tables A11 to A13 in essence yield a similar story to the quadratic trend filter. We see that while the results are relatively weaker for Brazil and Russia, the forecastability of Chinese stock market volatility is now observed for the short term even for the long-sample that includes the financial crisis and for the long term in the post-crisis era. Moreover, various output gap measures consistently predict Indian stock market volatility at all three forecast horizons across all three out-of-samples considered. In sum, the additional results show that stronger forecasting gains can be derived from the Hamilton (2018) filter, when compared to the quadratic trend filter used in the literature to derive measures of local, regional and global business cycles.[8]

Finally, for comparison purposes, we report in Table A14 the results for the U.S. stock market realized volatility under the quadratic trend, HP and Hamilton (2018) filters.[9] We observe that the findings for the U.S. stock market are quite similar to those of the BRICS, with forecastability observed primarily in the post crisis sub-sample due to business cycles in emerging economies and the overall world economy. In the case of the U.S. however, in terms of forecasting gains, the quadratic trend filter tends to outperform the other two, at medium- and long-runs, with the HP filter performing the worst.

[8]We also considered two other widely used detrending methods, namely the linear trend and the one-sided Christiano and Fitzgerald (2003) filter, to produce output gap measures, but the filter proposed by Hamilton (2018) consistently outperformed the other filters. Complete details of these results are available upon request from the authors.

[9]The data sample used for the U.S. is February 1990 to July 2018 and is obtained from the same sources as that of the BRICS.

5 Conclusion

This paper extends the emerging literature on the presence of a global financial cycle as a driver of financial conditions in emerging markets by exploring the role of business cycle proxies at the global, regional and local levels as potential predictors of stock market volatility in emerging nations. Building on the recent evidence that output gap serves as a business cycle indicator, we compute output gap measures at the domestic, regional and global levels for the major emerging nations in the BRICS and explore the out-of-sample predictive power of these business cycle proxies for stock market volatility in these countries. Our results show that while domestic output gap is important for India, Brazil and China, the business cycles associated with emerging and world economies are important for all the members of the bloc barring South Africa, particularly in the post global financial crisis period. The results are robust to whether we consider good or bad realized volatilities and the alternative filters to construct the measure of output gaps. While our findings imply that economic agents looking to invest in the BRICS equity markets can utilize regional and global business cycle proxies to improve the predictive accuracy of stock market volatility models, we also observe that these emerging nations display rather heterogeneous behavior in the relative role of idiosyncratic factors as a predictor of stock market volatility. Nevertheless, the findings suggest that despite the increase in the financial integration of world capital markets, emerging economies can still bear significant exposures to idiosyncratic risk factors, an issue of high importance for the profitability of global diversification strategies.

Table 1: Out-of-sample 1-month ahead realized volatility forecasting R^2_{OS} statistics

Model	Brazil	Russia	India	China	South Africa
Evaluation sample: 2005M1-2018M7					
OG_DOM	−0.858	−7.877	−4.255	4.055**	0.396
OG_WLDexUS	−2.358	−4.769	−4.628	−4.347	−1.880
OG_ADVexUS	−3.034	−6.102	−9.117	−3.247	−1.696
OG_EM	−1.932	−2.153	−0.477	−2.444	−1.404
OG_US	−10.705	−1.911	−4.362	−4.003	−11.227
OG_WLD	−4.421	−3.905	−0.870	−5.683	−2.663
First PC	−1.087	−8.891	−5.268	−4.159	−3.284
Maximum	−0.858	−1.911	−0.477	4.055**	0.396
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.754	−24.386	18.920**	−0.122	−2.549
OG_WLDexUS	−8.253	−5.819	−11.354	−5.093	−6.157
OG_ADVexUS	−16.627	−29.705	−34.589	−2.692	−7.577
OG_EM	3.588	18.504***	1.144*	0.034	−7.018
OG_US	−18.906	−9.956	−18.099	−4.684	−13.993
OG_WLD	2.830	4.710***	33.655***	−4.151	0.729
First PC	−2.900	−12.523	20.699***	−5.777	−7.032
Maximum	3.588	18.504***	33.655***	0.034	0.729
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−8.690	−36.454	50.464***	−0.351	−2.764
OG_WLDexUS	−9.247	4.087	−14.148	−1.308	−6.153
OG_ADVexUS	−24.789	−48.332	−75.809	−0.177	−11.197
OG_EM	3.660	41.039***	8.794***	−2.458	−5.204
OG_US	−11.699	−2.627	−11.024	−0.410	−5.566
OG_WLD	−1.800	0.875	28.152***	−4.622	−3.912
First PC	−11.199	−12.124	51.149***	−1.194	−6.821
Maximum	3.660	41.039***	51.149***	−0.177	−2.764

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 2: Out-of-sample 3-month ahead realized volatility forecasting R^2_{OS} statistics

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−2.679	1.122	0.412	3.992**	1.219
OG_WLDexUS	−0.535	−11.172	−9.817	−5.849	−3.584
OG_ADVexUS	−4.721	−18.928	−21.173	−7.189	−3.556
OG_EM	2.452	0.319	−1.766	0.446	−0.057
OG_US	−8.239	−8.564	−12.328	−8.659	−14.922
OG_WLD	1.022	−4.124	−0.770	−8.242	−3.662
First PC	−3.006	0.875	−2.105	−6.232	−7.042
Maximum	2.452	1.122	0.412	3.992**	1.219
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−33.614	−20.236	21.059***	−0.350	−12.600
OG_WLDexUS	−26.192	−18.784	−11.727	−6.291	−13.689
OG_ADVexUS	−59.114	−76.366	−38.165	−6.768	−20.050
OG_EM	6.405	43.267***	−1.148	1.198	−13.804
OG_US	−89.757	−56.136	−49.228	−11.094	−45.915
OG_WLD	5.566	10.514***	37.290***	−4.296	−0.474
First PC	−33.642	−25.886	19.970***	−8.038	−20.024
Maximum	6.405	43.267***	37.290***	1.198	−0.474
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−77.388	−43.216	52.323***	−1.367	−5.915
OG_WLDexUS	−28.181	6.023	−14.795	−1.514	−8.313
OG_ADVexUS	−91.707	−93.309	−90.993	−2.136	−25.032
OG_EM	−3.632	76.088***	−2.075	0.019	−7.550
OG_US	−53.849	−8.849	−38.844	−1.419	−15.340
OG_WLD	−10.378	6.162	35.127***	−3.701	−8.003
First PC	−89.198	−31.824	52.778***	−1.896	−13.247
Maximum	−3.632	76.088***	52.778***	0.019	−5.915

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 3: Out-of-sample 12-month ahead realized volatility forecasting R^2_{OS} statistics

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	4.933**	−9.262	7.166	2.614*	−0.017
OG_WLDexUS	−2.590	−11.762	−2.206	−8.019	−15.598
OG_ADVexUS	−9.428	−27.400	−24.877	−15.188	−11.568
OG_EM	3.597	3.981*	−1.313	2.367	3.959
OG_US	−17.190	−30.863	−33.532	−13.405	−70.016
OG_WLD	−2.004	−22.466	17.525***	−6.047	−33.284
First PC	0.790	−19.764	13.488***	−8.403	−35.493
Maximum	4.933**	3.981*	17.525***	2.614*	3.959
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	22.051***	−72.453	19.931*	0.675	−9.939
OG_WLDexUS	−32.087	−27.585	−17.847	−6.325	−14.990
OG_ADVexUS	−63.175	−122.947	−56.169	−17.990	−19.856
OG_EM	20.073**	57.480***	0.686	4.103	−22.746
OG_US	−132.292	−142.393	−139.024	−20.674	−96.447
OG_WLD	12.928***	21.548***	56.227***	1.535	3.824
First PC	10.814	−53.493	27.238***	−8.245	−24.963
Maximum	22.051***	57.480***	56.227***	4.103	3.824
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	2.879	−122.715	82.443***	6.488	−19.276
OG_WLDexUS	−21.543	20.503***	−8.939	−9.266	−1.960
OG_ADVexUS	−85.984	−113.478	−120.789	−41.302	−26.021
OG_EM	15.835	86.272***	23.259***	24.393***	−0.848
OG_US	−53.178	−21.146	−105.669	−32.964	−20.003
OG_WLD	12.842*	35.439***	67.704***	7.410*	−5.746
First PC	−8.548	−47.053	82.112***	−20.603	−12.968
Maximum	15.835	86.272***	82.443***	24.393***	−0.848

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

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A Appendix

A.1 Summary statistics

Table A1: Descriptive statistics

Brazil						Russia					
Variable	Mean	Std	Min	Max	ρ	Variable	Mean	Std	Min	Max	ρ
SR	0.883	6.379	-26.641	19.190	0.285	SR	1.571	9.215	-47.528	48.366	0.319
RV	0.522	0.760	0.023	6.877	0.532	RV	1.282	2.579	0.046	20.370	0.765
GoodRV	0.263	0.414	0.010	4.534	0.365	GoodRV	0.667	1.376	0.008	11.043	0.751
BadRV	0.259	0.411	0.009	3.873	0.549	BadRV	0.616	1.327	0.009	10.609	0.672
OG_DOM	0.000	8.900	-23.982	19.094	0.727	OG_DOM	0.000	6.942	-18.233	19.807	0.485
India						China					
Variable	Mean	Std	Min	Max	ρ	Variable	Mean	Std	Min	Max	ρ
SR	1.104	7.705	-28.779	43.820	0.363	SR	0.564	8.171	-30.037	53.916	0.284
RV	0.529	0.910	0.030	10.188	0.264	RV	0.767	1.713	0.013	22.764	0.295
GoodRV	0.264	0.574	0.010	9.269	0.147	GoodRV	0.413	1.351	0.006	20.247	0.134
BadRV	0.265	0.539	0.001	6.254	0.231	BadRV	0.354	0.574	0.001	4.875	0.423
OG_DOM	0.000	7.153	-11.612	32.312	0.608	OG_DOM	0.000	3.309	-10.828	15.359	0.640
South Africa						Regional and global output gap measures					
Variable	Mean	Std	Min	Max	ρ	Variable	Mean	Std	Min	Max	ρ
SR	0.890	4.601	-23.183	13.087	0.248	OG_WLDexUS	0.000	2.804	-11.190	5.793	0.968
RV	0.284	0.358	0.004	3.511	0.403	OG_ADVexUS	0.000	3.847	-14.517	7.317	0.972
GoodRV	0.137	0.139	0.001	0.945	0.449	OG_EM	0.000	2.858	-8.503	5.652	0.952
BadRV	0.147	0.254	0.001	2.566	0.262	OG_US	0.000	4.635	-15.620	8.456	0.984
OG_DOM	0.000	4.375	-12.886	13.816	0.853	OG_WLD	0.000	2.814	-8.046	8.632	0.972

ρ stands for the autocorrelation coefficient. All statistics except for the autocorrelation coefficient have been divided by 100.

A.2 Forecasting good and bad realized volatilities with output gaps

Table A2: Out-of-sample 1-month ahead good realized volatility forecasting R^2_{OS} statistics

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.533	−15.799	−4.579	3.661	0.031
OG_WLDexUS	−2.818	0.630	−7.153	−2.049	−1.257
OG_ADVexUS	−2.916	−1.063	−10.351	0.032	−1.636
OG_EM	−1.953	2.871	−0.519	1.004	−0.245
OG_US	−20.956	2.526	−0.426	−3.455	−8.851
OG_WLD	−5.176	2.315	−4.454	−3.175	−1.388
First PC	−0.539	−12.870	−9.450	−2.751	−2.259
Maximum	−0.533	2.871	−0.426	3.661	0.031
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	3.186	−29.668	21.379***	−0.894	−1.740
OG_WLDexUS	−7.552	−6.756	−1.522	−3.869	−1.939
OG_ADVexUS	−13.782	−29.841	−6.380	1.047	−3.134
OG_EM	7.737**	16.883***	−4.527	7.931***	−2.067
OG_US	−29.434	−12.482	13.943***	−5.698	−8.298
OG_WLD	3.184*	3.840**	13.058***	−2.344	0.788
First PC	2.097	−11.991	18.826***	−5.869	−2.937
Maximum	7.737**	16.883***	21.379***	7.931***	0.788
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−3.562	−28.121	60.412***	1.079**	−1.257
OG_WLDexUS	−8.585	1.561	−2.265	−1.393	−2.332
OG_ADVexUS	−21.089	−40.585	−15.551	2.714***	−5.749
OG_EM	8.250	31.781***	−22.733	9.625*	−0.934
OG_US	−18.350	−1.947	24.379***	−1.708	−4.907
OG_WLD	−3.853	−1.619	16.506***	−5.326	−0.898
First PC	−4.819	−0.840	54.283***	−2.615	−3.603
Maximum	8.250	31.781***	60.412***	9.625*	−0.898

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A3: Out-of-sample 3-month ahead good realized volatility forecasting R^2_{OS} statistics

Model	Brazil	Russia	India	China	South Africa
Evaluation sample: 2005M1-2018M7					
OG_DOM	−4.629	−1.185	0.603	5.091**	1.252
OG_WLDexUS	−2.466	−3.955	−11.291	−4.924	−0.267
OG_ADVexUS	−4.135	−9.023	−21.305	−5.081	−1.300
OG_EM	−0.457	4.104*	−1.725	3.278**	1.969
OG_US	−19.766	−3.719	−6.668	−8.689	−9.896
OG_WLD	−2.460	0.213	−5.250	−6.478	0.355
First PC	−6.956	−0.954	−3.860	−5.736	−1.830
Maximum	−0.457	4.104*	0.603	5.091**	1.969
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−21.027	−20.017	10.984***	−0.892	−6.989
OG_WLDexUS	−19.024	−15.982	−2.342	−6.619	−5.778
OG_ADVexUS	−35.473	−56.421	−12.038	−6.168	−9.060
OG_EM	9.710	34.479***	−8.072	7.679**	−5.386
OG_US	−86.843	−45.319	−7.445	−15.452	−23.135
OG_WLD	3.566	5.855*	14.941***	−3.325	−0.049
First PC	−20.242	−21.757	9.551***	−9.992	−9.214
Maximum	9.710	34.479***	14.941***	7.679**	−0.049
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−46.718	−44.251	30.510***	0.132	−1.462
OG_WLDexUS	−18.944	0.608	−2.949	−2.549	−2.812
OG_ADVexUS	−47.776	−70.953	−29.132	−3.283	−11.639
OG_EM	5.675	62.298***	−42.789	10.016*	−1.260
OG_US	−44.849	−10.878	1.339***	−4.396	−9.546
OG_WLD	−9.794	1.331	18.530***	−5.111	−1.734
First PC	−50.399	−27.970	27.515***	−4.868	−5.583
Maximum	5.675	62.298***	30.510***	10.016*	−1.260

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A4: Out-of-sample 12-month ahead good realized volatility forecasting R^2_{OS} statistics

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	5.118***	−12.396	−29.904	5.309***	2.653
OG_WLDexUS	−1.392	−1.768	1.800	−10.219	−12.049
OG_ADVexUS	−8.706	−14.844	−13.999	−17.686	−10.176
OG_EM	3.780	9.144***	−2.836	0.770	6.610
OG_US	−29.309	−19.214	−24.358	−14.499	−81.470
OG_WLD	−0.262	−4.789	20.132***	−5.481	−28.589
First PC	4.756**	−15.629	−2.843	−9.242	−27.133
Maximum	5.118***	9.144***	20.132***	5.309***	6.610
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	21.688***	−100.852	−78.148	3.919	−4.697
OG_WLDexUS	−31.582	−34.484	−17.328	−9.210	−10.166
OG_ADVexUS	−67.482	−137.440	−54.699	−29.849	−14.280
OG_EM	20.789**	58.275***	0.365	8.443**	−13.849
OG_US	−155.515	−160.200	−133.501	−40.516	−80.853
OG_WLD	14.136***	18.535***	58.609***	3.772*	−0.911
First PC	14.523**	−67.135	20.368***	−13.479	−18.095
Maximum	21.688***	58.275***	58.609***	8.443**	−0.911
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	8.167	−162.496	61.041***	11.225***	−10.837
OG_WLDexUS	−11.940	16.896***	−9.871	−13.136	0.737
OG_ADVexUS	−71.618	−133.460	−124.116	−69.220	−16.411
OG_EM	14.454	91.080***	19.640***	39.306***	0.483
OG_US	−45.907	−30.292	−104.790	−59.164	−17.778
OG_WLD	11.067*	32.314***	70.982***	12.819***	−1.252
First PC	0.944	−60.974	70.800***	−32.833	−7.505
Maximum	14.454	91.080***	70.982***	39.306***	0.737

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A5: Out-of-sample 1-month ahead bad realized volatility forecasting R^2_{OS} statistics

Model	Brazil	Russia	India	China	South Africa
Evaluation sample: 2005M1-2018M7					
OG_DOM	−1.753	−2.507	0.910	1.307	0.558
OG_WLDexUS	−2.121	−9.453	−2.556	−2.873	−2.914
OG_ADVexUS	−3.046	−10.404	−6.958	−3.420	−2.241
OG_EM	−1.928	−6.847	0.441	−2.431	−3.174
OG_US	−6.596	−8.198	−6.374	−2.876	−11.648
OG_WLD	−3.920	−11.133	1.039	−3.938	−4.218
First PC	−1.790	−3.876	0.616	−2.628	−4.349
Maximum	−1.753	−2.507	1.039	1.307	0.558
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−5.216	−21.136	15.732***	−0.208	−1.765
OG_WLDexUS	−6.424	−4.254	−18.951	−4.591	−9.940
OG_ADVexUS	−13.762	−28.972	−49.880	−4.173	−11.073
OG_EM	1.358	19.777***	2.604	−4.064	−12.118
OG_US	−9.236	−6.355	−41.193	−3.775	−18.766
OG_WLD	2.047	5.873***	33.780***	−4.556	1.000
First PC	−5.883	−12.227	13.111***	−4.574	−10.047
Maximum	2.047	19.777***	33.780***	−0.208	1.000
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−8.640	−32.910	24.502***	−1.343	−2.661
OG_WLDexUS	−4.669	6.863**	−19.635	−1.544	−7.870
OG_ADVexUS	−14.785	−45.034	−91.167	−1.014	−13.026
OG_EM	1.789	41.885***	21.124***	−5.330	−8.918
OG_US	−4.361	−1.439	−27.864	−0.143	−4.977
OG_WLD	1.022	3.770	23.214***	−4.510	−5.773
First PC	−10.273	−15.187	27.816***	−1.070	−7.481
Maximum	1.789	41.885***	27.816***	−0.143	−2.661

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A6: Out-of-sample 3-month ahead bad realized volatility forecasting R^2_{OS} statistics

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.027	1.060	2.258	0.508	0.901
OG_WLDexUS	−1.776	−14.231	−6.130	−3.568	−5.262
OG_ADVexUS	−6.689	−22.846	−15.890	−5.347	−5.030
OG_EM	0.805	−2.893	0.152	−0.655	−2.105
OG_US	−5.865	−11.628	−13.220	−5.001	−14.734
OG_WLD	−0.017	−7.112	1.672	−4.601	−6.106
First PC	−0.055	1.154	1.473	−3.966	−9.623
Maximum	0.805	1.154	2.258	0.508	0.901
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−20.794	−16.018	21.756***	−0.912	−14.012
OG_WLDexUS	−23.908	−15.159	−20.311	−2.950	−18.959
OG_ADVexUS	−59.001	−77.020	−57.010	−4.008	−27.040
OG_EM	2.480	43.975***	2.372	−0.185	−19.512
OG_US	−64.643	−53.881	−78.922	−5.759	−58.585
OG_WLD	5.042	14.384***	43.396***	−1.562	−0.600
First PC	−25.261	−23.375	20.013***	−3.756	−26.294
Maximum	5.042	43.975***	43.396***	−0.185	−0.600
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−43.636	−34.605	48.177***	−1.872	−7.975
OG_WLDexUS	−16.808	13.377**	−23.703	−0.365	−11.304
OG_ADVexUS	−68.382	−95.121	−121.027	−1.304	−30.407
OG_EM	−6.945	77.376***	24.247***	−0.332	−12.424
OG_US	−29.513	−3.944	−59.473	−0.838	−16.156
OG_WLD	−3.559	12.122*	34.406***	−0.501	−11.968
First PC	−53.799	−28.050	49.173***	−0.436	−16.353
Maximum	−3.559	77.376***	49.173***	−0.332	−7.975

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A7: Out-of-sample 12-month ahead bad realized volatility forecasting R^2_{OS} statistics

Model	Brazil	Russia	India	China	South Africa
		Evaluation sample: 2005M1-2018M7			
OG_DOM	3.020	−5.076	4.371***	0.050	−3.580
OG_WLDexUS	−8.661	−18.307	−7.490	−5.310	−15.849
OG_ADVexUS	−12.759	−34.782	−27.819	−10.278	−11.267
OG_EM	−4.006	−0.043	−0.449	2.019	−0.257
OG_US	−19.384	−35.991	−32.069	−9.565	−47.111
OG_WLD	−13.314	−31.486	6.716	−5.436	−30.469
First PC	−4.500	−15.052	7.805***	−6.332	−35.110
Maximum	3.020	−0.043	7.805***	2.019	−0.257
		Evaluation sample: 2010M1-2018M7			
Model	Brazil	Russia	India	China	South Africa
OG_DOM	13.447*	−45.558	15.227***	−1.094	−11.405
OG_WLDexUS	−23.384	−17.777	−19.390	−4.243	−15.344
OG_ADVexUS	−38.669	−98.331	−55.857	−10.739	−19.391
OG_EM	15.002**	53.241***	0.687	2.722	−24.260
OG_US	−79.144	−114.337	−136.495	−11.113	−87.477
OG_WLD	8.552**	23.384***	50.242***	1.176	7.526
First PC	3.924	−37.032	17.378***	−5.223	−24.898
Maximum	15.002**	53.241***	50.242***	2.722	7.526
		Evaluation sample: 2015M1-2018M7			
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−9.832	−83.778	33.883***	2.063	−18.467
OG_WLDexUS	−15.602	24.390***	−11.353	−5.648	−1.691
OG_ADVexUS	−40.535	−89.144	−116.889	−22.755	−24.432
OG_EM	8.558	80.271***	25.454***	15.771**	−0.178
OG_US	−26.132	−11.720	−104.842	−17.483	−16.271
OG_WLD	5.777	37.652***	61.165***	5.366	−5.275
First PC	−17.201	−30.919	50.052***	−11.781	−11.529
Maximum	8.558	80.271***	61.165***	15.771**	−0.178

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

A.3 Robustness checks

Table A8: Out-of-sample 1-month ahead realized volatility forecasting R^2_{OS} statistics (one-sided Hodrick and Prescott (1997) (HP) filter)

Model	Brazil	Russia	India	China	South Africa
Evaluation sample: 2005M1-2018M7					
OG_DOM	−0.641	−5.602	−9.294	−0.515	−0.746
OG_WLDexUS	−1.447	0.282	−1.258	−1.100	−0.080
OG_ADVexUS	−1.886	0.260	−1.422	−0.413	−0.540
OG_EM	0.085	0.075	−0.292	−2.551	0.643
OG_US	−6.329	5.069	−2.672	2.740	−1.219
OG_WLD	−6.840	0.050	−3.927	−0.200	−2.288
First PC	−0.461	−5.395	−9.584	−0.904	−1.694
Maximum	0.085	5.069	−0.292	2.740	0.643
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.469	−1.593	−9.088	−0.104	−2.451
OG_WLDexUS	−1.125	−2.792	−0.163	1.283***	−1.862
OG_ADVexUS	0.329	0.015	0.652	1.872***	−1.627
OG_EM	−6.348	−8.782	−0.443	0.208	−0.690
OG_US	−3.005	−29.006	0.750	6.015**	−7.389
OG_WLD	−4.894	−14.643	−1.292	1.594**	−6.979
First PC	−0.096	−0.756	−6.937	2.115***	−5.204
Maximum	0.329	0.015	0.750	6.015**	−0.690
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−1.793	1.291	−11.921	0.005	0.825
OG_WLDexUS	0.745	−13.725	−4.996	1.121***	3.812**
OG_ADVexUS	1.496	−7.371	−3.975	1.572***	3.622***
OG_EM	−2.705	−23.569	−6.008	0.256*	2.877**
OG_US	−6.831	−102.895	−31.475	4.376*	2.362
OG_WLD	1.001	−11.839	−3.547	1.528***	3.460**
First PC	0.398	−18.068	−2.765	1.803***	5.099*
Maximum	1.496	1.291	−2.765	4.376*	5.099*

The output gap is measured as the one-sided HP filtered natural log of industrial production. The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A9: Out-of-sample 3-month ahead realized volatility forecasting R^2_{OS} statistics (one-sided Hodrick and Prescott (1997) (HP) filter)

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−2.860	0.008	−10.846	0.067	−0.784
OG_WLDexUS	−5.647	0.995	0.957	−0.400	−1.351
OG_ADVexUS	−5.022	0.688	0.076	−0.247	−1.703
OG_EM	−4.021	1.552	3.130	−0.936	−0.411
OG_US	−9.355	−2.935	−0.765	1.065	−2.451
OG_WLD	−20.161	−6.012	−1.441	−1.301	−7.175
First PC	−2.176	−0.436	−11.563	−0.338	−4.129
Maximum	−2.176	1.552	3.130	1.065	−0.411
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−21.312	−2.355	−8.542	0.281	3.108
OG_WLDexUS	−0.001	0.398	−1.448	1.651***	−0.565
OG_ADVexUS	0.027	2.908	0.338	2.123***	−0.182
OG_EM	−8.129	−6.139	−2.432	0.499	−0.945
OG_US	4.071	−8.338	2.535	4.513**	1.339
OG_WLD	−1.608	−10.724	−3.468	1.396**	−5.281
First PC	−17.372	−2.726	−7.454	2.311***	0.095
Maximum	4.071	2.908	2.535	4.513**	3.108
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−44.914	−7.758	−12.791	0.875***	0.367
OG_WLDexUS	0.388	−11.462	−10.356	1.441***	2.090**
OG_ADVexUS	1.213	−6.494	−6.664	1.934***	2.061***
OG_EM	−5.441	−18.298	−13.505	0.443	1.097
OG_US	−0.396	−82.388	−26.430	2.503	5.781
OG_WLD	2.779*	−14.686	−6.418	1.201***	3.708***
First PC	−33.705	−20.427	−2.338	1.891**	4.054**
Maximum	2.779*	−6.494	−2.338	2.503	5.781

The output gap is measured as the one-sided HP filtered natural log of industrial production. The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A10: Out-of-sample 12-month ahead realized volatility forecasting R^2_{OS} statistics (one-sided Hodrick and Prescott (1997) (HP) filter)

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	1.097	−3.205	−1.412	0.017	−3.403
OG_WLDexUS	−1.568	−1.199	−5.282	−8.862	−1.199
OG_ADVexUS	−1.194	−1.703	−4.407	−14.184	−0.905
OG_EM	−2.239	−2.073	−5.413	−2.217	−1.157
OG_US	−3.909	−2.564	−8.666	−6.288	−1.624
OG_WLD	−0.103	−1.363	−13.161	−9.965	−2.179
First PC	0.841	−3.575	−2.032	−7.042	−3.765
Maximum	1.097	−1.199	−1.412	0.017	−0.905
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	0.851	−12.581	0.041	−1.032	5.009*
OG_WLDexUS	−11.952	−7.939	−4.440	−0.877	−2.751
OG_ADVexUS	−21.019	−19.534	−7.106	−0.730	−4.888
OG_EM	−2.482	−2.259	−2.151	−1.896	−1.377
OG_US	−39.246	−11.490	−7.027	−4.266	−7.160
OG_WLD	−20.930	−7.238	−4.610	−3.549	−5.095
First PC	−2.042	−13.462	−4.748	−2.497	−0.687
Maximum	0.851	−2.259	0.041	−0.730	5.009*
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−11.293	−5.355	−5.148	−1.133	5.440**
OG_WLDexUS	−0.745	0.956**	−2.444	−0.229	0.145*
OG_ADVexUS	−2.835	2.051**	−1.105	0.064	−0.172
OG_EM	0.732*	−5.174	−6.417	−0.105	0.433***
OG_US	4.992	−8.200	−12.153	−2.812	−0.494
OG_WLD	−0.277	3.902***	−0.277	−0.007	−0.688
First PC	−10.671	6.647	2.265	−0.364	1.299**
Maximum	4.992	6.647	2.265	0.064	5.440**

The output gap is measured as the one-sided HP filtered natural log of industrial production. The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A11: Out-of-sample 1-month ahead realized volatility forecasting R^2_{OS} statistics (Hamilton (2018) (Hamilton) filter)

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.442	−6.029	8.109*	14.209**	−1.410
OG_WLDexUS	−1.210	−7.772	4.634	13.243**	−1.138
OG_ADVexUS	−0.896	−8.140	3.265	12.281**	−0.988
OG_EM	−1.380	−6.592	6.638	14.706**	−1.192
OG_US	−4.080	−4.543	3.423	12.353**	−4.031
OG_WLD	−2.715	−6.348	5.552	13.721**	−0.917
First PC	−0.193	−6.512	6.009	13.343**	−0.752
Maximum	−0.193	−4.543	8.109*	14.706**	−0.752
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−5.240	−3.966	32.787***	12.948*	−2.592
OG_WLDexUS	−9.245	−1.240	18.518***	12.360*	−6.212
OG_ADVexUS	−5.456	−2.344	17.697***	12.536*	−4.841
OG_EM	−3.582	−1.586	21.151***	13.021*	−5.483
OG_US	−2.673	1.389	21.436***	13.562*	−3.257
OG_WLD	−4.236	−0.281	32.825***	10.976*	−3.924
First PC	−4.900	−1.001	28.849***	12.618*	−4.917
Maximum	−2.673	1.389	32.825***	13.562*	−2.592
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−8.021	3.384	41.648***	6.591	−0.784
OG_WLDexUS	−7.867	2.153	27.100***	7.562	−1.912
OG_ADVexUS	−9.483	−3.332	13.922**	6.780	−2.885
OG_EM	1.783	5.444*	26.565***	7.725	−1.278
OG_US	−2.131	10.741**	32.388***	7.661	0.435
OG_WLD	−4.902	6.365*	37.174***	6.584	−1.207
First PC	−5.064	2.536	35.978***	7.342	−1.286
Maximum	1.783	10.741**	41.648***	7.725	0.435

The output gap is measured as the Hamilton filtered natural log of industrial production. The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A12: Out-of-sample 3-month ahead realized volatility forecasting R^2_{OS} statistics (Hamilton (2018) (Hamilton) filter)

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.581	−3.998	6.936***	5.224	−0.996
OG_WLDexUS	0.719	−8.317	1.480	5.284	−0.370
OG_ADVexUS	0.706	−10.484	−1.095	4.607	−0.419
OG_EM	0.735	−3.567	4.041	6.142	−0.494
OG_US	1.147	−6.690	−0.443	5.141	−3.386
OG_WLD	2.073	−4.875	2.287	5.836	0.601
First PC	3.722	−5.289	3.032	5.185	0.563
Maximum	3.722	−3.567	6.936***	6.142	0.601
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−34.004	6.697*	50.424***	−0.173	−8.005
OG_WLDexUS	−30.451	−16.111	35.939***	0.238	−15.194
OG_ADVexUS	−17.904	−26.134	35.405***	0.250	−12.214
OG_EM	−5.480	7.906***	37.966***	1.735	−12.268
OG_US	−14.623	−16.393	38.153***	1.202	−14.034
OG_WLD	−15.828	−1.193	47.873***	−1.530	−9.520
First PC	−13.008	−0.840	44.934***	0.658	−14.067
Maximum	−5.480	7.906***	50.424***	1.735	−8.005
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−70.720	27.161***	56.837***	−8.533	−1.766
OG_WLDexUS	−20.145	4.045**	41.707***	−5.327	−0.803
OG_ADVexUS	−36.389	−51.912	30.309***	−6.938	−4.156
OG_EM	12.381*	34.879***	39.014***	−4.737	−0.526
OG_US	−16.270	−19.783	53.126***	−5.622	2.123
OG_WLD	−11.277	16.915***	54.026***	−5.384	0.455
First PC	−7.818	10.873***	52.210***	−5.412	−0.330
Maximum	12.381*	34.879***	56.837***	−4.737	2.123

The output gap is measured as the Hamilton filtered natural log of industrial production. The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table A13: Out-of-sample 12-month ahead realized volatility forecasting R^2_{OS} statistics (Hamilton (2018) (Hamilton) filter)

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	1.973**	−2.807	5.907*	−6.351	−2.936
OG_WLDexUS	−2.203	−12.028	4.528	−17.043	−6.555
OG_ADVexUS	0.792	−14.963	5.920**	−18.750	−5.046
OG_EM	−3.449	−1.830	0.863	−7.661	−0.458
OG_US	2.912	−13.725	3.896*	−14.787	−25.090
OG_WLD	0.563	−13.792	8.967***	−27.981	−10.629
First PC	3.603	−7.788	8.765***	−16.863	−7.291
Maximum	3.603	−1.830	8.967***	−6.351	−0.458
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	13.162**	−31.490	42.480***	4.276	−26.604
OG_WLDexUS	−55.277	−98.180	23.861***	−13.373	−50.573
OG_ADVexUS	−10.298	−94.688	26.328***	−6.476	−31.103
OG_EM	−16.916	−21.593	30.670***	−0.673	−43.060
OG_US	−9.679	−101.370	23.681***	1.517	−40.970
OG_WLD	−38.236	−60.092	37.288***	−10.424	−46.299
First PC	−12.914	−49.059	37.440***	−5.377	−47.029
Maximum	13.162**	−21.593	42.480***	4.276	−26.604
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	29.912**	6.588	52.181***	30.036***	−9.720
OG_WLDexUS	−3.117	−25.659	41.698***	18.285***	1.862
OG_ADVexUS	−9.784	−111.256	33.730***	1.063	−0.056
OG_EM	28.159***	22.501***	41.663***	33.370***	−1.558
OG_US	−1.058	−127.048	63.337***	5.868	13.414***
OG_WLD	5.816*	5.400	59.768***	20.088***	0.706
First PC	25.992***	−7.026	57.698***	17.018***	1.202
Maximum	29.912**	22.501***	63.337***	33.370***	13.414***

The output gap is measured as the Hamilton filtered natural log of industrial production. The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

A.4 Additional analysis: The case of the US

Table A14: Out-of-sample 1-, 3- and 12-month ahead realized volatility forecasting R^2_{OS} statistics of the US

	Quadratic trend			HP filter			Hamilton filter		
Evaluation sample: 2005M1-2018M7									
Model	1-month	3-month	12-month	1-month	3-month	12-month	1-month	3-month	12-month
OG_DOM	−6.757	−2.158	−12.035	4.15	−4.367	−12.878	−1.307	−1.439	2.785
OG_WLDexUS	−2.571	0.887	7.003*	0.166	−1.452	−8.52	−0.789	−0.003	−0.383
OG_ADVexUS	−4.948	−0.916	−2.65	−0.47	−1.608	−7.905	−1.468	−0.098	0.759
OG_EM	0.216	−4.95	1.649	0.825	−0.864	−4.306	−1.63	−3.363	−7.703
OG_US	−6.757	−2.158	−12.035	4.15	−4.367	−12.878	−1.307	−1.439	2.785
OG_WLD	−3.694	2.154	9.566*	−0.833	−10.645	−11.941	−0.82	0.692	2.956
First PC	−5.067	−0.984	−1.505	1.169	−4.52	−13.474	−0.88	−0.051	1.655
Maximum	0.216	2.154	9.566*	4.15	−0.864	−4.306	−0.789	0.692	2.956
Evaluation sample: 2010M1-2018M7									
	Quadratic trend			HP filter			Hamilton filter		
Model	1-month	3-month	12-month	1-month	3-month	12-month	1-month	3-month	12-month
OG_DOM	−2.259	−35.104	−144.645	−28.47	−52.21	−56.164	−0.746	−3.855	−29.749
OG_WLDexUS	−1.227	−12.218	−20.239	−4.41	−6.857	−15.046	−2.296	−2.806	−51.373
OG_ADVexUS	−3.398	−25.706	−41.781	−4.034	−4.729	−8.969	−2.033	−6.574	−37.827
OG_EM	0.393	1.57	−9.662	−2.078	−5.15	−10.019	−1.548	0.162	−21.866
OG_US	−2.259	−35.104	−144.645	−28.47	−52.21	−56.164	−0.746	−3.855	−29.749
OG_WLD	1.838	3.583	5.595	−12.517	−30.866	−5.433	−1.076	0.315	−53.179
First PC	−2.959	−29.433	−81.107	−12.896	−23.392	−28.868	−1.526	−3.487	−43.964
Maximum	1.838	3.583	5.595	−2.078	−4.729	−5.433	−0.746	0.315	−21.866
Evaluation sample: 2015M1-2018M7									
	Quadratic trend			HP filter			Hamilton filter		
Model	1-month	3-month	12-month	1-month	3-month	12-month	1-month	3-month	12-month
OG_DOM	−3.032	−39.014	−161.183	−27.614	−39.482	−46.386	−2.706	1.561	20.874***
OG_WLDexUS	−5.081	−15.36	−4.924	0.877	−1.475	−6.128	−1.322	0.389	4.918***
OG_ADVexUS	−22.021	−85.959	−138.39	1.888	0.199	−1.763	−4.417	−13.936	−14.42
OG_EM	5.353	21.714*	57.483***	−0.191	−2.334	−9.017	−1.743	5.945***	18.406***
OG_US	−3.032	−39.014	−161.183	−27.614	−39.482	−46.386	−2.706	1.561	20.874***
OG_WLD	3.205	14.769	56.073***	1.233	−4.479	−0.125	0.398	10.687***	33.100***
First PC	−8.92	−50.761	−121.667	−3.056	−8.865	−14.589	−0.914	3.557	19.106***
Maximum	5.353	21.714*	57.483***	1.888	0.199	−0.125	0.398	10.687***	33.100***

The R^2_{OS} statistics (in percent) capture the proportional reduction in the mean squared error of the forecasting model augmented with alternative output gap measures relative to the benchmark model. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.