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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

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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.

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 rela-

[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), where we found 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.

tive 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 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 coeffi-

[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`.

cients.

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 average of monthly realized volatilities,[5] i.e.,

$$RV_{t+h} = \alpha + \beta_m RV_t + \beta_q RVQA_t + \gamma OG_t + \epsilon_{t+h}, \text{ for } t = 3, ..., T_0 - h, \tag{2}$$

where the quarterly average of monthly realized volatilities is defined as

$$RVQA_t = \frac{1}{3}\left(RV_t + RV_{t-1} + RV_{t-2}\right). \tag{3}$$

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 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

[5] We also considered annual average of monthly realized volatilities, but the coefficient corresponding to it, was generally insignificant, and hence, was dropped from the specification.

volatility as

$$\widehat{RV}_{T_0+h} = \widehat{\alpha} + \widehat{\beta}_m RV_{T_0} + \widehat{\beta}_q RVQA_{T_0}. \tag{4}$$

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.,

$$MSE(h) = \frac{1}{T - T_0 - h + 1} \sum_{t=T_0}^{T-h} \left(\widehat{RV}_{t+h} - RV_{t+h} \right)^2, \tag{5}$$

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

$$R^2_{OS}(h) = 1 - \frac{MSE(h)_{augmented}}{MSE(h)_{benchmark}}. \tag{6}$$

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.[6]

Three different forecast evaluation sample 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-

[6] 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.

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.[7]

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. For monthly data, 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.

The results presented in Tables A8 to A13 in essence yields a similar story to the quadratic

[7] 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.

trend filter. When the one-sided HP filter is used, the forecasting error is consistently reduced particularly for Brazil, Russia, India, and to a lesser extent China and even South Africa (at the longest horizon), irrespective of the output gap measure used to augment the benchmark model, especially for the post crisis out-of-samples. However, given the strong concerns raised by Hamilton (2018), one must be cautious about the strong results derived under the HP-filter. Given this in mind, examining the results from the Hamilton (2018) filter, we see that while the results are relatively weaker for Brazil, the forecastability of Chinese stock market volatility is now observed for the short- and medium-terms even for the long-sample that includes the financial crisis. The results for Russia, India and South Africa do tend to carry over from the HP filter to the Hamilton (2018) filter case. In sum, the additional results show that stronger forecasting gains can be derived from the HP and Hamilton (2018) filters, 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 crises 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 filters proposed by Hodrick and Prescott (1997) and 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	0.246	−0.948	−4.433	1.640	−0.115
OG_WLDexUS	−3.845	−0.158	−5.321	−2.519	−4.605
OG_ADVexUS	−4.021	1.149	−9.266	−3.864	−3.439
OG_EM	−1.989	0.736	−0.594	1.362	−2.323
OG_US	−10.433	0.285	−4.087	−0.157	−12.022
OG_WLD	−4.899	−2.177	−1.456	−3.507	−5.416
Maximum	0.246	1.149	−0.594	1.640	−0.115
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	3.243	−6.057	21.980**	0.230	−1.376
OG_WLDexUS	−11.716	−1.915	−18.606	−3.773	−5.587
OG_ADVexUS	−15.999	8.417***	−39.317	−4.196	−5.593
OG_EM	5.785*	22.864***	−0.113	2.318**	−6.258
OG_US	−16.984	7.971***	−18.610	0.714	−11.753
OG_WLD	0.386	−0.687	26.876***	−3.160	1.380
Maximum	5.785*	22.864***	26.876***	2.318**	1.380
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−1.583	−2.359	49.050***	−2.683	−1.460
OG_WLDexUS	−8.538	0.306	−20.197	−0.383	−5.145
OG_ADVexUS	−14.253	26.313***	−71.328	1.332**	−7.641
OG_EM	10.251	52.553***	7.661***	2.345*	−3.248
OG_US	−4.866	7.534**	−9.844	0.752	−5.122
OG_WLD	−3.258	−3.295	21.083***	−3.583	−2.552
Maximum	10.251	52.553***	49.050***	2.345*	−1.460

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	−1.242	−1.636	0.971	2.542	−1.581
OG_WLDexUS	−7.222	−0.284	−11.483	−6.381	−10.626
OG_ADVexUS	−8.272	0.549	−21.655	−10.027	−8.062
OG_EM	−2.502	5.397***	−2.236	2.400	−2.531
OG_US	−15.424	−1.600	−12.331	−5.364	−16.560
OG_WLD	−4.951	0.538	−1.999	−7.899	−10.384
Maximum	−1.242	5.397***	0.971	2.542	−1.581
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−17.914	−13.592	24.729***	−0.363	−7.483
OG_WLDexUS	−34.809	−13.881	−18.244	−8.148	−12.699
OG_ADVexUS	−48.989	−10.603	−41.475	−10.590	−14.788
OG_EM	12.067**	44.193***	−2.128	4.252**	−12.571
OG_US	−81.026	−14.304	−46.438	−7.368	−37.193
OG_WLD	−1.791	−2.775	28.224***	−4.694	1.512
Maximum	12.067**	44.193***	28.224***	4.252**	1.512
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−55.401	−11.606	49.210***	−3.533	−1.222
OG_WLDexUS	−25.000	−2.110	−18.842	−1.028	−5.031
OG_ADVexUS	−47.708	13.050***	−76.892	−0.033	−14.839
OG_EM	18.124	78.881***	−6.320	4.039	−3.789
OG_US	−30.369	1.991**	−31.280	−1.283	−10.215
OG_WLD	−12.273	−5.596	25.465***	−4.308	−6.165
Maximum	18.124	78.881***	49.210***	4.039	−1.222

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	5.058^{***}	-6.012	8.759^{*}	4.776^{***}	0.446
OG_WLDexUS	-4.627	-4.320	-3.946	-9.011	-5.782
OG_ADVexUS	-9.677	-14.465	-20.091	-15.371	-4.170
OG_EM	0.602	7.977^{***}	-1.497	0.834	5.497
OG_US	-16.704	-18.715	-26.399	-16.308	-13.604
OG_WLD	-5.398	-5.169	15.766^{***}	-6.526	-12.049
Maximum	5.058^{***}	7.977^{***}	15.766^{***}	4.776^{***}	5.497
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	14.380^{*}	-53.787	25.337^{**}	2.859^{*}	-5.761
OG_WLDexUS	-54.691	-37.354	-30.062	-8.355	-12.595
OG_ADVexUS	-87.371	-100.895	-62.865	-18.284	-13.994
OG_EM	5.273	48.979^{***}	-2.563	5.380^{**}	-25.297
OG_US	-183.421	-125.912	-123.892	-21.879	-68.744
OG_WLD	-1.420	0.520	44.228^{***}	1.605	5.360
Maximum	14.380^{*}	48.979^{***}	44.228^{***}	5.380^{**}	5.360
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-5.570	-48.970	80.110^{***}	4.882	-9.926
OG_WLDexUS	-25.653	1.396	-19.516	-5.982	3.571
OG_ADVexUS	-92.343	-72.716	-109.741	-29.205	-23.034
OG_EM	1.987	78.137^{***}	19.977^{***}	26.202^{***}	10.854
OG_US	-61.307	-19.620	-90.683	-19.192	-31.842
OG_WLD	7.585	11.866^{**}	53.483^{***}	9.421^{***}	10.161
Maximum	7.585	78.137^{***}	80.110^{***}	26.202^{***}	10.854

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	−1.145	−3.798	−4.848	0.507	−0.573
OG_WLDexUS	−4.105	0.901	−6.791	1.766	−3.043
OG_ADVexUS	−4.484	3.161	−9.230	−0.047	−2.900
OG_EM	−1.039	2.352	−0.675	−2.542	−0.754
OG_US	−18.180	0.962	0.355	5.426**	−8.773
OG_WLD	−5.138	−0.878	−4.453	−0.405	−3.251
Maximum	−1.039	3.161	0.355	5.426**	−0.573
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	2.114	0.262	24.762***	2.121*	−1.449
OG_WLDexUS	−11.351	1.084**	−1.799	0.082	−2.081
OG_ADVexUS	−15.661	17.019***	−5.572	−1.169	−2.601
OG_EM	8.495***	22.199***	−4.131	−1.935	−1.729
OG_US	−25.240	6.733***	16.316***	10.298***	−6.664
OG_WLD	0.127	−0.717	10.270***	−2.551	0.493
Maximum	8.495***	22.199***	24.762***	10.298***	0.493
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−1.085	−1.056	56.629***	−4.976	−0.782
OG_WLDexUS	−7.399	1.587**	−1.718	3.251***	−2.022
OG_ADVexUS	−12.215	37.543***	−9.799	12.045***	−3.754
OG_EM	13.803*	50.619***	−20.286	−1.402	−0.751
OG_US	−7.126	8.630***	26.986***	10.833***	−3.604
OG_WLD	−4.742	−2.678	11.684***	−5.411	−0.851
Maximum	13.803*	50.619***	56.629***	12.045***	−0.751

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

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-2.337	-2.409	0.964	0.991	-1.010
OG_WLDexUS	-6.884	1.161	-11.146	-1.452	-4.723
OG_ADVexUS	-6.333	2.929	-19.910	-3.986	-3.923
OG_EM	-3.379	9.080^{***}	-1.883	2.160	0.262
OG_US	-26.704	-2.306	-6.002	1.918	-9.473
OG_WLD	-5.782	2.114	-5.285	-1.427	-3.971
Maximum	-2.337	9.080^{***}	0.964	2.160	0.262
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-7.364	-12.960	11.605^{***}	3.016^{*}	-5.763
OG_WLDexUS	-26.014	-8.895	-2.707	-6.300	-6.169
OG_ADVexUS	-33.169	3.313	-11.657	-9.385	-7.426
OG_EM	13.888^{**}	43.122^{***}	-7.674	5.443^{***}	-5.403
OG_US	-79.247	-4.178	-4.957	1.907	-17.370
OG_WLD	-1.875	-2.542	11.871^{***}	-3.147	-0.356
Maximum	13.888^{**}	43.122^{***}	11.871^{***}	5.443^{***}	-0.356
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-31.931	-9.547	26.803^{***}	-6.990	-0.494
OG_WLDexUS	-16.745	-0.799	-2.239	0.086	-2.191
OG_ADVexUS	-26.286	27.834^{***}	-20.805	7.552^{***}	-6.976
OG_EM	19.713	78.405^{***}	-40.147	11.394^{***}	-1.347
OG_US	-26.045	5.033^{***}	6.535^{***}	7.000^{*}	-5.205
OG_WLD	-10.401	-4.867	13.500^{***}	-5.473	-2.782
Maximum	19.713	78.405^{***}	26.803^{***}	11.394^{***}	-0.494

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	3.048***	−8.774	−18.062	5.198**	3.422
OG_WLDexUS	−3.798	−3.373	−1.270	−11.402	0.173
OG_ADVexUS	−9.488	−15.481	−14.156	−16.490	−0.951
OG_EM	0.755	11.210***	−2.670	−5.931	7.790*
OG_US	−27.591	−19.766	−22.256	−19.653	−10.031
OG_WLD	−3.941	−2.653	17.625***	−3.024	−3.395
Maximum	3.048***	11.210***	17.625***	5.198**	7.790*
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	16.404***	−69.883	−26.625	5.453***	−1.815
OG_WLDexUS	−50.730	−39.287	−25.365	−12.858	−6.819
OG_ADVexUS	−86.914	−108.171	−57.132	−31.188	−8.650
OG_EM	7.808	51.438***	−1.164	8.160***	−14.943
OG_US	−206.244	−129.444	−113.017	−38.020	−51.629
OG_WLD	2.769	1.121	47.099***	3.397*	3.208
Maximum	16.404***	51.438***	47.099***	8.160***	3.208
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	3.433	−59.666	78.235***	7.409***	−2.743
OG_WLDexUS	−14.765	2.206	−16.659	−10.776	5.069
OG_ADVexUS	−75.071	−80.124	−103.114	−49.339	−9.780
OG_EM	2.281	83.203***	14.841***	30.081***	6.363
OG_US	−51.346	−20.702	−81.200	−32.854	−15.173
OG_WLD	7.092	12.300**	56.720***	12.043***	6.594
Maximum	7.092	83.203***	78.235***	30.081***	6.594

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

Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.390	−2.046	0.829	−1.109	0.044
OG_WLDexUS	−3.517	−1.044	−3.875	−2.387	−6.184
OG_ADVexUS	−3.706	−0.298	−7.549	−2.904	−4.137
OG_EM	−2.175	−0.114	0.014	−0.231	−4.628
OG_US	−6.617	−0.931	−5.869	−1.366	−13.670
OG_WLD	−4.554	−2.921	0.058	−2.874	−7.576
Maximum	−0.390	−0.114	0.829	−0.231	0.044
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.181	−15.708	14.391***	−0.023	−0.569
OG_WLDexUS	−8.301	−5.865	−26.249	−2.527	−9.045
OG_ADVexUS	−11.691	−1.874	−49.649	−2.314	−8.280
OG_EM	2.859	24.716***	−1.350	0.198	−11.325
OG_US	−8.433	7.822***	−35.338	−0.433	−17.381
OG_WLD	0.710	−0.865	26.060***	−1.939	2.543
Maximum	2.859	24.716***	26.060***	0.198	2.543
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−3.782	−9.301	22.275***	−2.817	−1.532
OG_WLDexUS	−4.956	−1.031	−25.155	−0.387	−7.131
OG_ADVexUS	−8.868	13.471***	−79.819	0.267	−9.791
OG_EM	4.255	55.390***	16.702***	−0.049	−5.493
OG_US	−1.961	6.296*	−22.783	−0.095	−5.962
OG_WLD	−0.616	−4.445	17.273***	−1.796	−3.913
Maximum	4.255	55.390***	22.275***	0.267	−1.532

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

Model	Brazil	Russia	India	China	South Africa
Evaluation sample: 2005M1-2018M7					
OG_DOM	0.183	−0.937	2.680	1.777	−1.999
OG_WLDexUS	−8.838	−2.292	−8.557	−5.392	−13.210
OG_ADVexUS	−10.398	−2.614	−16.781	−7.388	−10.043
OG_EM	−2.847	2.778**	−0.610	−0.759	−5.162
OG_US	−11.035	−1.807	−12.869	−5.670	−18.581
OG_WLD	−6.319	−0.961	0.016	−7.234	−13.732
Maximum	0.183	2.778**	2.680	1.777	−1.999
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−10.543	−12.360	25.526***	−0.655	−6.830
OG_WLDexUS	−28.090	−18.008	−30.297	−4.785	−17.448
OG_ADVexUS	−40.920	−23.777	−59.548	−5.875	−19.990
OG_EM	9.047*	42.898***	−1.747	−0.001	−18.019
OG_US	−55.585	−21.998	−71.808	−6.699	−51.946
OG_WLD	0.104	−2.889	31.963***	−3.402	3.178
Maximum	9.047*	42.898***	31.963***	−0.001	3.178
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−31.920	−11.954	47.003***	−1.252	−2.031
OG_WLDexUS	−14.841	−3.587	−29.641	−0.415	−7.302
OG_ADVexUS	−31.826	−2.264	−102.789	−0.818	−19.272
OG_EM	10.298	76.813***	16.393***	−0.499	−6.178
OG_US	−15.743	−0.530	−50.247	−1.056	−13.343
OG_WLD	−5.186	−6.236	25.416***	−1.890	−8.406
Maximum	10.298	76.813***	47.003***	−0.415	−2.031

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	2.919	−3.777	4.062***	2.254**	−1.946
OG_WLDexUS	−7.499	−4.732	−6.307	−6.097	−6.933
OG_ADVexUS	−11.418	−13.068	−18.957	−10.736	−4.604
OG_EM	−1.901	5.371***	−0.168	1.553	2.568
OG_US	−12.748	−16.423	−21.512	−9.756	−10.621
OG_WLD	−10.434	−6.413	7.507**	−6.967	−12.158
Maximum	2.919	5.371***	7.507**	2.254**	2.568
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	1.395	−38.621	15.084***	1.366	−8.586
OG_WLDexUS	−40.752	−34.398	−32.611	−4.512	−14.458
OG_ADVexUS	−59.897	−91.044	−62.934	−9.418	−15.517
OG_EM	2.335	44.226***	−4.438	2.513	−27.460
OG_US	−111.628	−115.685	−122.076	−11.438	−65.880
OG_WLD	−3.884	−0.160	38.371***	1.076	6.087
Maximum	2.335	44.226***	38.371***	2.513	6.087
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−20.416	−39.250	30.279***	3.316	−15.176
OG_WLDexUS	−20.015	0.115	−21.950	−2.241	0.576
OG_ADVexUS	−51.156	−66.864	−107.922	−14.037	−29.904
OG_EM	−0.684	72.164***	23.324***	15.966**	12.088
OG_US	−32.752	−18.887	−92.142	−10.538	−38.741
OG_WLD	1.630	10.883**	47.531***	6.987***	10.761
Maximum	1.630	72.164***	47.531***	15.966**	12.088

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)

		Evaluation sample: 2005M1-2018M7			
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−3.929	−7.301	2.305	0.393	0.057
OG_WLDexUS	−3.362	−18.698	1.970	−34.088	−1.092
OG_ADVexUS	−2.965	−19.897	0.883	−32.840	−0.305
OG_EM	−3.433	−12.540	1.898	−33.406	−1.313
OG_US	−1.971	−21.777	0.613	−36.731	−0.022
OG_WLD	−4.224	−17.822	1.199	−34.237	−1.058
Maximum	−1.971	−7.301	2.305	0.393	0.057
		Evaluation sample: 2010M1-2018M7			
Model	Brazil	Russia	India	China	South Africa
OG_DOM	1.673	50.904***	53.732***	0.740	−13.150
OG_WLDexUS	9.871**	40.897***	46.749***	10.680*	−14.481
OG_ADVexUS	7.299***	22.052**	27.692***	8.143	−11.317
OG_EM	9.988**	48.494***	55.285***	11.201*	−14.088
OG_US	4.400**	3.216	26.542***	0.260	−9.150
OG_WLD	9.077***	50.024***	42.214***	10.842**	−14.423
Maximum	9.988**	50.904***	55.285***	11.201*	−9.150
		Evaluation sample: 2015M1-2018M7			
Model	Brazil	Russia	India	China	South Africa
OG_DOM	0.253	69.602***	63.354***	0.806	−5.274
OG_WLDexUS	11.627	44.686**	61.771***	−1.030	−3.537
OG_ADVexUS	10.818*	46.984**	42.125***	0.202	−4.551
OG_EM	11.479	59.701***	66.134***	−0.456	−2.645
OG_US	7.431**	63.531***	35.674***	−4.869	−3.605
OG_WLD	11.209*	64.243***	55.713***	0.534	−3.342
Maximum	11.627	69.602***	66.134***	0.806	−2.645

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	−7.987	−14.700	4.833	0.027	−1.143
OG_WLDexUS	−6.711	−45.488	4.582	−59.936	−3.366
OG_ADVexUS	−5.472	−45.880	2.108	−56.772	−1.327
OG_EM	−7.143	−32.163	4.081	−58.292	−4.006
OG_US	−4.000	−51.650	1.195	−61.103	−0.320
OG_WLD	−9.027	−45.520	2.698	−61.084	−3.534
Maximum	−4.000	−14.700	4.833	0.027	−0.320
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.203	77.425***	66.240***	0.184	−26.718
OG_WLDexUS	20.608***	72.817***	56.305***	13.748*	−29.786
OG_ADVexUS	14.869***	43.357***	33.836***	10.973*	−22.781
OG_EM	20.847***	80.419***	66.454***	14.283**	−29.209
OG_US	8.570***	10.602	31.816***	−0.012	−18.293
OG_WLD	18.901***	80.660***	50.889***	14.076**	−29.601
Maximum	20.847***	80.660***	66.454***	14.283**	−18.293
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.989	92.369***	78.938***	−0.557	−7.979
OG_WLDexUS	25.008**	73.964***	76.299***	−5.189	−5.344
OG_ADVexUS	23.148***	81.057***	52.425***	−2.056	−6.667
OG_EM	24.700**	85.629***	81.584***	−4.238	−4.059
OG_US	15.028***	75.117***	44.152***	−9.990	−4.556
OG_WLD	24.260**	90.823***	68.918***	−1.944	−4.938
Maximum	25.008**	92.369***	81.584***	−0.557	−4.059

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	−18.607	−21.210	0.212	−3.427	−2.398
OG_WLDexUS	−15.847	−35.116	−1.574	−55.989	−7.843
OG_ADVexUS	−11.829	−26.623	−3.152	−43.681	−3.284
OG_EM	−17.830	−38.854	−3.842	−65.118	−9.802
OG_US	−8.121	−25.292	−3.030	−41.980	−0.771
OG_WLD	−19.328	−41.944	−4.862	−57.703	−8.434
Maximum	−8.121	−21.210	0.212	−3.427	−0.771
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−16.035	37.693***	58.299***	−1.025	−53.206
OG_WLDexUS	0.749	49.039***	55.593***	−3.771	−60.253
OG_ADVexUS	−1.150	9.741***	30.403***	−1.209	−40.036
OG_EM	−1.589	55.119***	68.266***	−4.692	−65.956
OG_US	−3.446	−26.424	29.460***	−1.746	−31.681
OG_WLD	−1.812	37.395***	49.712***	−4.280	−60.482
Maximum	0.749	55.119***	68.266***	−1.025	−31.681
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−1.359	61.175***	79.113***	11.331**	−30.239
OG_WLDexUS	18.094**	87.113***	78.763***	6.648	−18.037
OG_ADVexUS	7.279***	38.334***	48.888***	1.911	−19.815
OG_EM	19.384**	89.027***	86.651***	8.981	−14.561
OG_US	−0.842	−34.603	43.276***	0.559	−18.326
OG_WLD	15.189***	73.394***	70.594***	5.032	−16.280
Maximum	19.384**	89.027***	86.651***	11.331**	−14.561

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	−3.500	−44.056	2.254	8.878*	−1.950
OG_WLDexUS	−4.122	−45.986	−0.699	9.572*	−1.998
OG_ADVexUS	−3.635	−45.808	−1.755	8.693*	−2.059
OG_EM	−4.291	−44.862	1.317	10.131**	−1.112
OG_US	−7.113	−40.698	−1.490	8.211	−5.258
OG_WLD	−6.013	−45.152	−0.323	8.957*	−1.502
Maximum	−3.500	−40.698	2.254	10.131**	−1.112
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	0.043	23.050***	−4.708	15.330*	−1.525
OG_WLDexUS	−3.363	28.168***	−12.682	15.358**	−5.472
OG_ADVexUS	0.355	31.890***	−14.227	15.900**	−4.555
OG_EM	−1.187	20.180***	−8.950	15.251**	−4.454
OG_US	2.009**	34.783***	−10.390	15.759**	−3.236
OG_WLD	−1.303	24.442***	−7.108	14.432*	−3.563
Maximum	2.009**	34.783***	−4.708	15.900**	−1.525
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−0.121	20.554***	4.573	4.690	−0.054
OG_WLDexUS	−1.267	28.755***	−8.885	5.663	−1.614
OG_ADVexUS	1.491	48.213***	−13.424	5.666	−2.355
OG_EM	2.490	13.359***	−9.169	5.786	−0.749
OG_US	2.612*	49.717***	−9.434	5.391	−0.271
OG_WLD	−0.690	25.912***	−5.817	5.303	−1.102
Maximum	2.612*	49.717***	4.573	5.786	−0.054

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)

Model	Brazil	Russia	India	China	South Africa
Evaluation sample: 2005M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-1.768	7.109	4.866^{*}	14.540^{**}	-1.803
OG_WLDexUS	-2.199	4.526	-0.623	15.153^{**}	-3.511
OG_ADVexUS	-1.363	3.800	-2.996	14.460^{**}	-3.685
OG_EM	-2.537	7.414	2.442	16.148^{***}	-1.400
OG_US	-1.078	7.011	-3.619	14.237^{**}	-7.788
OG_WLD	-2.279	5.630	-0.715	14.684^{**}	-2.238
Maximum	-1.078	7.414	4.866^{*}	16.148^{***}	-1.400
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-4.940	38.128^{***}	39.555^{***}	17.754^{**}	-6.619
OG_WLDexUS	-14.161	33.841^{***}	26.330^{***}	17.694^{**}	-14.200
OG_ADVexUS	-2.346	34.961^{***}	24.539^{***}	17.971^{**}	-12.033
OG_EM	-1.243	39.372^{***}	30.551^{***}	18.742^{**}	-10.503
OG_US	-3.458	37.016^{***}	23.923^{***}	17.989^{**}	-14.881
OG_WLD	-7.291	34.312^{***}	31.180^{***}	16.455^{**}	-8.815
Maximum	-1.243	39.372^{***}	39.555^{***}	18.742^{**}	-6.619
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	-14.184	38.442^{***}	42.575^{***}	-0.698	-0.364
OG_WLDexUS	-4.832	38.463^{***}	28.829^{***}	1.742	-0.054
OG_ADVexUS	-4.029	43.213^{***}	23.079^{***}	0.829	-2.411
OG_EM	12.795^{***}	41.100^{***}	28.605^{***}	2.304	1.164
OG_US	-0.258	45.142^{***}	32.493^{***}	1.241	1.536
OG_WLD	-2.139	36.789^{***}	33.477^{***}	2.137	0.860
Maximum	12.795^{***}	45.142^{***}	42.575^{***}	2.304	1.536

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	−4.250	−5.976	4.991*	−14.127	−3.007
OG_WLDexUS	−7.461	−14.968	2.025	−21.287	−5.545
OG_ADVexUS	−4.956	−19.149	3.006	−23.814	−3.688
OG_EM	−9.037	−4.103	−0.560	−11.845	0.066
OG_US	−1.006	−16.995	−0.357	−20.013	−15.579
OG_WLD	−2.810	−19.122	5.195*	−28.668	−9.127
Maximum	−1.006	−4.103	5.195*	−11.845	0.066
Evaluation sample: 2010M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	−1.035	−8.275	41.640***	1.437	−28.850
OG_WLDexUS	−86.611	−52.717	14.769***	−16.813	−53.356
OG_ADVexUS	−33.805	−53.218	15.319***	−7.979	−34.793
OG_EM	−41.260	9.925**	27.078***	−4.052	−43.787
OG_US	−29.857	−59.919	8.225*	0.157	−42.723
OG_WLD	−66.527	−32.651	24.032***	−12.146	−47.365
Maximum	−1.035	9.925**	41.640***	1.437	−28.850
Evaluation sample: 2015M1-2018M7					
Model	Brazil	Russia	India	China	South Africa
OG_DOM	23.118	22.541***	48.079***	18.155***	−5.894
OG_WLDexUS	−8.523	10.682***	34.852***	5.590*	5.565*
OG_ADVexUS	−20.058	−39.776	26.288***	−9.384	0.564
OG_EM	22.167***	40.314***	39.652***	21.584***	9.431***
OG_US	−5.041	−49.409	47.549***	−0.761	17.446***
OG_WLD	−0.030	14.120***	45.861***	10.011***	9.345***
Maximum	23.118	40.314***	48.079***	21.584***	17.446***

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	−6.363	−2.652	−0.080	0.825	0.996	3.125	−1.777	−2.048	1.838
OG_WLDexUS	−2.876	−0.411	6.244*	0.636	−2.384	−7.108	−2.101	−0.525	−1.618
OG_ADVexUS	−5.424	−3.860	3.042	0.907	−0.179	−0.195	−2.925	−1.475	1.406
OG_EM	−0.057	0.591	2.163	0.450	−3.261	−10.263	−3.472	0.111	−8.875
OG_US	−6.363	−2.652	−0.080	0.825	0.996	3.125	−1.777	−2.048	1.838
OG_WLD	−3.858	0.758	6.647	0.737	−2.707	−7.959	−1.640	−0.033	−3.261
Maximum	−0.057	0.758	6.647	0.907	0.996	3.125	−1.640	0.111	1.838
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	−0.244	−22.855	−83.038	−4.918	−22.682	−67.537	−1.248	−3.688	−24.118
OG_WLDexUS	−0.531	−10.843	−13.730	−9.552	−39.521	−119.197	−2.593	−3.520	−35.766
OG_ADVexUS	−1.630	−19.145	−26.822	−6.708	−29.646	−81.788	−2.186	−6.650	−31.207
OG_EM	0.506	1.886	2.484	−9.506	−37.599	−120.823	−2.622	−1.609	−14.223
OG_US	−0.244	−22.855	−83.038	−4.918	−22.682	−67.537	−1.248	−3.688	−24.118
OG_WLD	1.933**	2.893	9.873*	−9.645	−39.955	−116.399	−1.811	−0.985	−35.690
Maximum	1.933**	2.893	9.873*	−4.918	−22.682	−67.537	−1.248	−0.985	−14.223
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	1.300*	−25.465	−106.920	−18.854	−55.439	−139.675	−2.695	−2.472	3.583
OG_WLDexUS	−4.436	−15.942	−10.875	−22.540	−63.755	−153.773	−1.279	−3.705	−7.171
OG_ADVexUS	−12.083	−57.090	−88.248	−25.134	−72.364	−154.480	−2.768	−13.510	−21.732
OG_EM	3.627*	21.752***	53.312***	−18.309	−50.473	−129.610	−3.642	0.774	5.051***
OG_US	1.300*	−25.465	−106.920	−18.854	−55.439	−139.675	−2.695	−2.472	3.583
OG_WLD	3.277	16.483*	59.341***	−23.199	−65.658	−146.276	−1.439	2.987	14.266***
Maximum	3.627*	21.752***	59.341***	−18.309	−50.473	−129.610	−1.279	2.987	14.266***

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.