Commodity Prices and Forecastability of South African Stock Returns Over a Century: Sentiments versus Fundamentals

Afees A. Salisu* and Rangan Gupta**

Abstract

We forecast real stock returns of South Africa over the monthly period of 1915:01 to 2021:03 using real oil, gold and silver prices, based on an autoregressive type distributed lag model that controls for persistence and endogeneity bias. Oil price proxies for fundamentals, while gold and silver prices capture sentiments. We find that the metrics for fundamentals and sentiments both predict real stock returns of South Africa, with nonlinearity, modelled by decomposing these prices into their respective positive and negative counterparts, playing an important role in terms of forecasting when a longer out-of-sample period spanning over three-quarters of a century is used. When compared to fundamentals, sentiments, particularly real gold prices, have a relatively stronger role to play in forecasting real stock returns. Further, the predictability of stock returns emanating from fundamentals and sentiments is in line with the findings over the same period derived for two other advanced markets namely, the United Kingdom (UK) and the United States (US), but the stock market of another emerging economy, i.e., India covering 1920:08 to 2021:03, unlike South Africa, is found to be completely unpredictable. In other words, South Africa, in terms of its predictability, behaves like a developed stock market. Finally, given the importance of platinum and palladium for South Africa, our forecasting exercise based on their real prices over 1968:01 to 2021:03, depicts strong predictive content for real stock returns, thus again highlighting the importance of behavioral variables. However, these prices do not necessarily contain additional information over what is already available in gold, silver and oil real prices. Our results have important implications for academicians, investors and policymakers.

Keywords: Commodity prices, real stock returns, emerging and developed markets, forecasting

JEL Codes: C22, C53, G15, G17, Q02

* Corresponding author. Centre for Econometric and Allied Research, University of Ibadan, Ibadan, Nigeria. Email: adebare1@yahoo.com.

** Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: rangan.gupta@up.ac.za.

1. Introduction

On one hand, practitioners in finance require real-time forecasts of stock returns for asset allocation, while on the other hand, academics are particularly interested in stock return forecasts due to important implications associated with producing robust measures of market efficiency, which in turn helps to develop more realistic asset pricing models (Gupta et al., 2017; 2018). Naturally, the existing literature on forecasting international stock returns, based on a wide array of (linear and nonlinear) models and (macroeconomic, financial, technical and behavioral) predictors, is vast to say the least. Note that, providing a detailed review is beyond the scope of this paper, and also not our main objective, but the interested reader is referred to the recent works of, for example, Rapach and Zhou (2013), Bannigidadmath and Narayan (2015), Sousa et al., (2016), Aye et al., (2017a), Jordan et al., (2017), Phan et al., (2018), Christou and Gupta (2020), Christou et al., (2021), to get an idea about this ever burgeoning area of research.

In sum, the major points from the existing literature can be highlighted as follows: First, while the early studies concentrated on forecasting stock markets of developed economies, the strong performance of the equity markets of many emerging economies from around the 1990s, with their stock returns far exceeding those of industrial financial markets, has led to many studies being also devoted to forecasting stock returns of emerging countries. This is understandable, since the emerging markets have started providing diversification opportunities to investors, and are also of interest to academicians in terms of comparing their characteristics with developed economies. Having said all this, historical forecasting analyses of important emerging stock markets, spanning longest possible data samples (such as, over centuries), to track their evolution, and to avoid the sample selection bias, are rare, when compared to their developed counterparts. This is indeed to some extent driven by the lack of continuous historical data on both stock prices and its relevant predictors. Second, a large information set in terms of combining the predictive content of a vast number of predictors appear to be required in order to successfully challenge standard benchmark model forecasts. Third, stock return predictions using atheoretical techniques, which tend to exploit information on the recent behavior of stock prices based on statistical approaches, as well as machine learning and computational intelligence techniques, typically tend to perform better than theoretically motivated empirical models.

Keeping the above points in mind, the primary objective of this paper is to forecast real stock returns for an emerging market namely, the All Share Stock Index (ALSI) of South Africa, over the monthly period of 1915:01 to 2021:03, with the establishment of the Johannesburg

Stock Exchange (JSE) dating as far back as 1887. The choice of South Africa as a case study of an emerging economy is driven not only by the availability of stock market data spanning over a century, but also because, as stressed by Mensi et al., (2014, 2016), the need to conduct a standalone analysis of the South African equity market is warranted due to its sophistication, along with the fact that it is one of the largest exporters of highly financialized strategic commodities like, coal, chrome, diamond, gold, ilmenite, iron ore, manganese, palladium, platinum, rutile, vanadium, vermiculite, and zirconium (Ashman et al., 2013; Cakan and Gupta, 2017; Naik et al., 2018). The performance of the stock market is naturally closely tied to the overall economy (Gupta and Hartley, 2013; Aye et al., 2013a, 2015, 2019), and the accurate forecasting of returns would entail valuable leading information to the policymakers in terms of designing optimal policies. It must be noted that, while there exist quite a few studies on out-of-sample prediction of South African stock prices and/or (excess) returns (see for example, Gupta and Modise (2012a, 2013a), Wen et al., (2015); Gupta et al., (2016); Bouri et al., (2020)), highlighting the role of combined information of macroeconomic and financial predictors, but unlike our paper, these works have looked at data basically spanning only the last three decades.

While historical equity market forecasting has its advantages in avoiding sample selection bias by tracking the evolution of predictability over the longest possible data available, it also comes with a major challenge. Specifically in terms of data availability on the wide array of predictors that have been shown to affect global stock returns, especially when it involves emerging economies, as indicated above. Given this, one would need to be innovative in finding proxies that can capture information of not only macroeconomic and financial fundamentals, but also behavioral variables. In this regard, historical values of the West Texas Intermediate (WTI) real oil price available at monthly frequency from 1871:01, can understandably serve as a good proxy for macroeconomic and financial predictors. This is because of its ability to affect the stock market through changes in expected cash flows and/or the discount rate, output, monetary and fiscal policy decisions, as well as macroeconomic and financial uncertainties (Degiannakis et al., 2018; Smyth and Narayan, 2018). In the context of South Africa, the significant impact of oil shocks on wide array of recent movements of economic and financial variables (including the stock market) is quite well-established (see for example, Gupta and Modise (2013b), Chisadza et al., (2016), Aye et al., (2017b), Balcilar et al., (2017, 2018a), Salisu and Gupta (2021), Salisu et al., (2021)), and hence can be expected to be an encapsulating metric for the information contained in such predictors.

At the same time, the behavioral theory of finance and related empirical studies have firmly established the effect of investor sentiment on stock returns, which tend to suggest that investors are not immune to behavioural biases, and hence, can be overly optimistic or pessimistic relative to fundamentals, and hence can lead to irrational market outcomes, i.e., speculative market sentiment can cause stock prices to diverge from their fundamental values (see, Gebka (2014) and Balcilar et al., (2018b) for detailed reviews). Therefore, to incorporate the role of behavioral factors, something that has completely been ignored in the South African stock returns forecasting literature,[1] we consider real gold and silver prices, monthly data of which are available from 1915:01, and hence determines the starting period of our analysis (given that the JSE ALSI is available from 1910). The decision to look at these two precious metal prices in capturing information about time-variation in sentiment or investor risk preferences is motivated by the work of Jordan et al., (2018),[2] and emanates from the logic that gold and silver are considered as safe havens traditionally (see, Boubaker et al., (2020) for a historical analysis in this regard from 1257 for gold and 1687 for silver). In other words, gold and silver tend to offer portfolio-diversification and/or hedging benefits during periods of weak investor sentiment and/or uncertainty, and hence would result in higher prices due to increased demand. So higher gold and silver prices resulting from their higher demand is expected to be negatively correlated with stock prices, whose prices tend to decline due to their lower demand, as investors perceive equities to be unsafe investment as risk aversion increases. Besides, gold and silver, as part of additional analyses, we also consider the role of real platinum and palladium prices over more than half a century (1968:01-2021:03), with the former also well established as having safe haven properties (Huang and Kilic, 2019). In this regard, according to the Central Intelligence Agency (CIA)'s World Factbook, South Africa is the largest producer of platinum, and comes second (after Russia) in terms of Palladium, with it ranked eighth in gold production. Naturally, this provides added motivation to look at South Africa as our case study. At this stage, we must keep in mind that while higher precious metals prices depicting weaker investor sentiment is expected to reduce stock returns, for a major exporter of gold, palladium and platinum like South Africa, increased prices of these commodities is also likely to boost the state of the domestic economy. This can then increase investment in the stock market by domestic investors, and hence arrest part of the initial decline in the longer-

[1] Though some in-sample evidence of predictability of sentiment for the JSE ALSI returns have been reported by Solanki and Seetharam (2014), Dalika and Seetharam (2015), and Rupande et al., (2019).
[2] These authors used nonferrous industrial metals namely, aluminum, copper, nickel and platinum, to proxy for fundamental predictors.

run. But, it is probably safe to assume that the initial decline in stock returns due to weakening of global sentiments as signaled by increases in precious metals prices will dominate the latter effect of recovery in the equity market.

In addition, given the availability of data spanning over a century as well for two advanced markets namely, the United Kingdom (UK) and the United States (US) over 1915:01 to 2020:03, and the emerging market of India over 1920:08 to 2021:03, we are able to compare with these economies our forecasting results for South Africa derived under real oil, gold and silver prices. Further, with the well-established fact that international stock returns, including that of South Africa, are related to these predictors in a nonlinear manner (Gupta and Modise, 2012b; Aye et al., 2013b; Guidolin et al., 2009; Gupta et al., 2019; 2020), we use the approach of Shin et al., (2014), to decompose overall oil and precious metals prices into their respective positive and negative components. In this manner, we are able to test asymmetry in the forecasting capabilities of our predictors, emanating from their differential information and/or possible good and bad news content. Understandably, the positive (negative) component of oil and precious metals prices would be indicative of bad (good) news due to possible recessionary (expansionary) and inflationary (deflationary) impact of the former, along with higher (lower) interest rate to fight inflation (deflation), and weaker (stronger) investor sentiments due to the latter.

It is well-established that in-sample predictability does not guarantee out-of-sample forecasting gains emanating from a specific predictor, and it is in fact the latter exercise that tends to provide a more robust test of the appropriateness of an econometric model and associated predictors (Campbell, 2008). Given this, we are the first paper to provide a comprehensive forecasting analysis of real stock returns of India, South Africa, the UK and the US spanning over a century of data, based on well-grounded proxies of fundamentals and sentiments, by simultaneously accounting for nonlinearity to bring in completeness to our analysis. In this regard, as far as the econometric framework is concerned, we use the Westerlund and Narayan (2012, 2015)-type distributed lag model, since it simultaneously incorporates observed salient features of the data, such as persistence and endogeneity bias, which have been shown to affect forecasting performance, if ignored.

The remainder of the paper is organized as follows: Section 2 lays out the methodology, while Section 3 presents the data and the empirical results, with Section 4 concluding the paper.

2. Methodology

We construct an empirical model that examines the role of fundamentals and sentiments in stock return predictability while accounting for salient data features. We therefore set out to forecast the stock returns over a century for South Africa, as well as India, the UK and the US as additional analyses. As previously noted, we use the WTI oil price as a proxy for fundamentals while the prices of precious metals namely, gold and silver (as well as palladium and platinum for South Africa), are distinctly used to capture sentiments. We draw from the Westerlund and Narayan (2012, 2015)-type distributed lag model framework that simultaneously incorporates persistence and endogeneity bias that may affect the forecast outcome, if ignored. The framework has already been widely applied to stock return predictability[3] (see, Narayan and Gupta (2015), Phan et al., (2015), Narayan et al., (2018), Salisu et al., (2019c, 2019d)).

The possible endogenety bias resulting from the restricted model for stock returns that considers only the researcher's predictor(s) of interest, while neglecting other possible predictors, is resolved within the estimation process. Hence, the WN-type distributed lag models of stock returns involving fundamentals and sentiments are respectively specified in equations (1) and (2) as:

$$r_t = \alpha + \beta_1 fdmtl_{t-1} + \beta_2 \left(fdmtl_t - \rho fdmtl_{t-1} \right) + \varepsilon_t \quad (1)$$

$$r_t = \alpha + \beta_1 snt_{t-1} + \beta_2 \left(snt_t - \rho snt_{t-1} \right) + \varepsilon_t \quad (2)$$

where r_t is the country's stock returns at time t; α is the intercept; $fdmtl_t$ is a measure of fundamentals (WTI real oil price); snt_t is a measure of sentiments (real gold, silver, palladium, or platinum prices); β_1 is the slope coefficient that measures the predictability of the incorporated measure of fundamentals/sentiments; the additional term $\beta_2 \left(fdmtl_t - \rho\left(fdmtl_{t-1} \right) \right)$ or $\beta_2 \left(snt_t - \rho\left(snt_{t-1} \right) \right)$ is incorporated to correct for any resultant endogeneity bias (and by extension persistence effect) that is occasioned by the fundamentals/sentiments being correlated with the error term (ε_t). All the predictors are expressed in logs.

[3] Several studies have also used the model for forecasting macro variables and exchange rates (see for example, Salisu et al., (2018a, 2018b, 2019a, 2019b, 2021), Tule et al., (2019, 2020)).

To account for nonlinearity, following Shin et al., (2014), let us define x_t as denoting our predictors, i.e., *fdmtl*$_t$ or *snt*$_t$, which is then decomposed as: $x_t = x_0 + x_t^+ + x_t^-$ where x_t^+ and x_t^- are the partial sum processes of positive and negative changes in x_t:

$$\boldsymbol{x}_t^+ = \sum_{j=1}^{t} \Delta \boldsymbol{x}_t^+ = \sum_{j=1}^{t} \max(\Delta \boldsymbol{x}_j, 0), \qquad \boldsymbol{x}_t^- = \sum_{j=1}^{t} \Delta \boldsymbol{x}_t^- = \sum_{j=1}^{t} \min(\Delta \boldsymbol{x}_j, 0)$$

Then in equations (1) and (2), instead of the overall values of the proxies of fundamentals and sentiments, we use either their positively- or negatively-decomposed values as predictors.[4]
We estimate the models in two main steps. An appropriate model structure is first determined using information on the observed data characteristics. We thereafter specify a predictive model that incorporates one period lag of fundamentals/sentiments and simultaneously account for salient data features,[5] as well as time-dependence in parameters using rolling window approach. Thereafter, we compare the forecast performance of our predictive model with that of the benchmark model (which is the conventional autoregressive $AR(p)$ model, where p denotes an optimal lag order that is chosen based on the Akaike information criterion (AIC)). In other words, the paired forecast errors of our predictive model and the autoregressive model are compared using the Diebold and Mariano (DM, 1995) statistic. The DM test gives a formal and statistical basis for conclusion of outperformance, given that it tests the hypothesis that the forecast errors of the paired models do not differ markedly or their paired difference is not statistically different from zero. The test statistic is specified in equation (3) as:

$$DM\ Stat = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{3}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the sample mean of the loss differential $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$ with respective loss functions $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ of the forecast errors, ε_{it} and ε_{jt} that are associated with forecasts $\hat{r}_{it}$ and $\hat{r}_{jt}$, respectively; and $V(d_t)$ is the unconditional variance of d_t. The null hypothesis involves relative equality of the forecast errors of the competing

[4] A number of studies have shown that stock returns respond asymmetrically to fundamentals (oil price) (see for example, Narayan and Gupta (2015), Smyth and Narayan (2018), Salisu and Isah (2017), Salisu et al., (2019c)) and we further advance the literature to examine such possibility for sentiments particularly from the out-of-sample predictability perspective

[5] Westerlund and Narayan (2012, 2015) details the computational procedure of the methodology.

models: $E\left[d_t\right]=0$. A rejection of the null hypothesis would imply that the forecast accuracy of the two competing models are statistically different.

3. Data and preliminary analysis

The Johannesburg Stock Exchange (JSE) All Share Index (ALSI), i.e. JSE-ALSI, as well as the Bombay Stock Exchange (BSE) Index of India, UK FTSE ALSI, and the US S&P500 Composite Stock Index data are used based on their long-span data availability. The local currency stock indexes of South Africa, India and the UK are converted to US dollars by using the bilateral dollar-based exchange rates (except for the S&P500 Composite Index), and then divided by the US Consumer Price Index (CPI), to get to the real stock prices. The data for the stock indexes, exchange rates, and US CPI are obtained from Global Financial Data (https://globalfinancialdata.com/). We then compute the log-returns of the real stock prices. The WTI oil price in US dollars is also deflated by the US CPI and then is logged, with the raw oil price data also sourced from Global Financial Data. The nominal gold and silver prices in US dollars are derived from Macrotrends at: https://www.macrotrends.net/, and then are converted to real terms by dividing with the US CPI, which we use in log-terms. The nominal palladium and platinum prices are obtained from: https://www.kitco.com/, and also converted to real terms using the US CPI data, and considered in the model in their respective logarithmic-forms. The nominal gold and silver prices data starts from 1915:01, and it defines the starting point of the analysis for South Africa, the UK and the US. For India, stock returns data starts from 1920:08. Further, since palladium and platinum data is available from 1968:01, the analysis for South Africa involving these two additional precious metals is conducted over a shorter sample period beginning at this date. Our analyses end in 2021:03, which was the last available data point for all our variables at the time of writing this paper.

Having outline the sources, we probe the data for its characteristic features with respect to its distribution, stationarity/unit root, conditional heteroskedasticity, serial correlation and persistence. We therefore present the results of the descriptive and preliminary analysis in Table 1, for the stock returns of the four countries considered as well as the log of the predictors (prices of gold, silver, palladium, platinum and oil (WTI)). For the periods covered in this study, all the stock returns except that of the US are on average negative, with the returns of South Africa and the US being the most and least volatile, respectively. On average, the logged metals prices range between 1.068 and 2.745, corresponding to silver and gold, the least and most expensive, respectively, among the considered precious metals. While all the returns are negatively skewed and leptokurtic, the logged predictors are most positively skewed (except for platinum) and platykurtic (except for silver and palladium). While the logged metals prices exhibit unit roots, stock returns and logged oil price are stationary and may be better fitted using model with constant and trend. Our dataset exhibits evidence of persistence, conditional heteroskedasticity (except for gold price and stock returns of India), and serial correlation (except for the Indian stock returns) up to the 12th lag. The above-observed data characteristics largely favour the WN-type distributed lag model and is therefore considered suitable for our analysis.

[INSERT TABLE 1]

4. Empirical Results

In this segment, we concentrate on the out-of-sample forecasting exercise of real stock returns of South Africa, using overall real WTI oil price, and real gold and real silver prices, and their respective decomposition into the positive and negative series. We also report the results, as a matter of comparison, for India, the UK and the US. We rely on a rolling-window approach, whereby the overall samples are split into two in- and out-of-sample periods involving 75% and 25% of the data respectively, and the reverse, i.e., 25% and 75% respectively. The first break-up of the overall data is in line with the studies on South Africa, cited above, that have looked at data starting around 1990, while the latter allows for a longer out-of-sample period spanning over three-quarters of a century. Table 2, reports the one-sided Diebold and Mariano (1995) test statistics, where we compare the forecast performance of our predictive model with the benchmark, i.e., the *AR(p)*, as well as performance of the real prices of gold or silver relative to the real oil price, given the lack of studies related to South Africa on the role of sentiment indicators, with all focus thus far on fundamentals as predictors. The idea is to see if proxies of fundamentals and sentiments add to the forecasting ability of an autoregressive model or real stock returns, and if this is the case, then whether sentiments perform better than fundamentals.[6]

[6] We also conducted in-sample predictability analysis based on the overall sample period, and our results were generally in line with intuition. The negative and positive values of WTI and gold significantly (at the 1% level) increased and decreased real stock returns respectively, suggesting that stronger (weaker) fundamentals and sentiments associated with negative (positive) values of oil and gold prices would tend to boost (dampen) the South African equity market. The negative values of platinum and palladium are also found to be positively related to real stock returns in a statistically significant manner at the 1% level, but this is not observed to be the case under the positive values. As far as silver is concerned, both negative and positive values are shown to reduce real stock returns significantly at the 1% level, though the decline is much stronger under the positive values associated with weaker sentiments. In sum, the in-sample results tend to suggest that gold is perhaps a better proxy for sentiments compared to the other precious metals. Complete details of these results are available upon request from the authors.

As observed from Table 2, looking first at the case of South Africa, under the 75:25 split, real gold, real silver, and real oil prices all significantly outperform the benchmark at the 1% level at the forecast horizon of 3-, 6-, and 12-month-ahead. With the WTI oil price summarizing the effect of many fundamental variables on stock prices, the evidence of predictability emanating from the real oil price is consistent with earlier results obtained for South Africa. This is because, existing studies (see in particular, Gupta et al., (2016)) have highlighted the importance of combining information from various fundamental predictors in forecasting the equity market in South Africa. The result continues to hold when we look at the negative and positive values of the predictors. Interestingly, when we compare the performance of the sentiment proxies with oil price, i.e., the measure of fundamentals, gold tends to outperform oil strongly at the 1% level of significance, and silver weakly at the 10% level, with this pattern for gold continuing under both negative and positive values of the decomposed series of real gold prices. For silver, strong gains at the 5% level relative to oil is observed under the positive values only, i.e., when both sentiments proxied by positive real silver prices and fundamentals captured by positive real oil prices are weak. The reverse holds true under negative values, i.e., oil has stronger forecasting ability than silver for real stock returns at the 5% level, if we now considered the real silver price-based model as our benchmark, which would then just invert the sign of the one-sided DM test to negative. These results tend to suggest that sentiments, in particular real gold prices, carry stronger forecasting ability than fundamentals for South Africa, under both linear and nonlinear specifications, i.e., irrespective of whether gold prices are increasing or decreasing, with stronger gains under the latter.

When we compare South Africa with another emerging market namely, India, we find that the real equity returns are unpredictable for the latter based on the information content of the predictors capturing both fundamentals and sentiments. In fact, if we reverse the benchmarks to the models with predictors, the *AR(p)* outperforms the former group in a statistically significant manner at 1% level of significance. When we turn to the advanced market of the UK, the performance of gold compared to the benchmark stands out at the 1% level when we consider overall prices, but decomposition of oil, gold and silver real prices into their respective positive and negative values all outperform the benchmark. The importance of overall gold prices, unlike silver, as a measure of sentiments, is further highlighted, when we find statistically significant gains at the 1% level relative to fundamentals, i.e., real oil prices. Though when we look at decomposed values, silver and gold prices outperform WTI oil price under negative values, at least at the 5% level of significance, with oil holding greater predictive ability than the two precious metals prices when all prices are rising (if the benchmark model is that of sentiments and not fundamentals), characterizing an overall weak investment environment. For the US, both fundamentals and sentiments hold predictive content for real stock returns, as does their respective decomposed values by beating the benchmark forecasts in a statistically significant manner at the 1% level. When we compare across fundamentals and sentiments, the latter dominates at the 1% level under overall prices, and silver under positive values only. In other words, if we reverse the benchmark from fundamentals to sentiments, the role of oil relative to gold and silver when prices are all negative, i.e., fundamentals have more predictive content than sentiments, especially when prices are declining, depicting expansionary economy and strong investor sentiments.

Next, for the sake of robustness, we also considered a 25:75 ratio of the sample period involving the in- and out-of-sample respectively. The predictive abilities of overall real gold and real oil prices observed above relative to the benchmark continue to hold for South Africa under the longer out-of-sample period at the 1% level of significance. Interestingly, silver also plays a role at the 1% level along with the other two predictors, when we decompose the prices into their positive and negative values, highlighting the importance of accounting for nonlinearity in the model when considering a long out-of-sample period. Overall, positive real gold prices outperform the WTI real oil price at least at the 5% level of significance, while the same holds true for declines in real silver prices. But, the important role of fundamentals relative to sentiments captured by silver prices, cannot be ignored. The predictors continue to fail to predict the Indian real stock returns, with now UK being added to the list, suggesting that out-of-sample predictability of the stock market of the UK based on predictors associated with fundamentals and sentiments are a more recent event, when one puts these results into perspective relative to the ones discussed above. Just like under the smaller out-sample, overall and decomposed real oil, gold and silver prices continue to depict evidence of predictability for the US under the longer out-of-sample period, with sentiments dominating fundamentals except when prices are increasing.

[INSERT TABLE 2]

As an additional analysis, given the importance of platinum and palladium to the South African economy, we also investigated the importance of the real prices of these two precious metals in forecasting the economy's real stock returns over 1968:01 to 2021:03. As shown in Table 3, these two metals, which can also be considered as alternative metrics of sentiments, also outperform the benchmark *AR(p)* model at all forecasting horizons, irrespective of whether we use a 75:25 or 50:50 in- and out-of-sample split. However, these precious metals cannot provide any additional predictive information over the forecasts generated during this period by real oil, gold and silver prices, as suggested by the insignificant DM test statistics. In fact, if the benchmarks are inverted to platinum and palladium, then oil, gold and silver will, in general, statistically dominate the other two precious metals.

[INSERT TABLE 3]

5. Conclusion

In this paper, we forecast the real stock returns of South Africa spanning over a century of data, i.e., 1915:01 to 2021:03 for the first time. To incorporate the role of fundamentals and sentiments, we use the information contained in real oil prices, and real gold and silver prices respectively, as proxies, due to unavailability of data on economic, financial and behavioral predictors over such a long data span. We also decompose the prices into their positive and negative components to model nonlinearity in their relationships with stock returns. Using an autoregressive type distributed lag model that controls for persistence and endogeneity bias, we draw the following conclusions: (a) Real stock returns of South Africa is indeed predictable based on the information contained in fundamentals proxied by real oil price, and sentiments captured by real gold and silver prices; (b) Nonlinearity, in terms of forecastability, matters more, when we consider a long out-of-sample period involving over three-quarters of a century of data, compared to a shorter out-of-sample period. But the significant role of both fundamentals and predictors continues to hold irrespective of the length of the out-of-sample period, highlighting that that the South African stock market has always been forecastable over its entire historical evolution; (c) When compared to fundamentals, i.e., real oil price, sentiments as captured by real gold price movements particularly, tend to matter more for forecasting real stock returns of South Africa; (d) When compared to another emerging market i.e., India over 1920:08 to 2021:03, and two other advanced economies of the UK and the US, spanning 1915:01 to 2021:03, South Africa tends to behave similar to that of the latter group, in the sense of fundamentals and sentiments depicting predictability. Interestingly, Indian stock market is completely unpredictable based on the three prices considered, and the US equity market in particular has a role for fundamentals over sentiments unlike South Africa, especially when nonlinearity is allowed; (e) When we investigate the role of platinum and palladium real prices over 1968:01 to 2021:03, given its importance to the South African economy, they are indeed found to contain significant predictive ability for the real stock returns of South Africa, and hence once again highlights the role of behavioral factors in driving the equity market. However, these prices do not necessarily contain additional information over what is already available in real prices of gold, silver and oil. In sum, the decision to study South African equity returns forecasting in a standalone sense as the focus of our paper is vindicated due to it depicting properties similar to advanced markets, i.e., financial sophistication, which in fact formed the initial motivation of our forecasting exercise.

Our results have important implications for academics, international investors looking at South Africa as an option to diversify their portfolios, and also the policymakers. First, when developing asset price models for South Africa, the role of nonlinearity and behavioral factors, in addition to fundamentals, need to be accounted for. In other words, the South African equity market is inefficient, at least in the semi-strong sense. Given this, investors should also keep in mind the role of sentiments in driving South African stock returns, over and above fundamentals. But more importantly, with the market being predictable, information on oil, gold and silver real prices can be used to design the optimal weight of investment in the South African equity market in a portfolio. Finally, with stock markets known to lead the macroeconomy of South Africa, its monthly forecasts can be fed into mixed data sampling (MIDAS) models to predict the future path of quarterly variables, like the real Gross Domestic Product (GDP), i.e., policymakers can conduct nowcasting given a predictable domestic stock market.

Given that, both fundamentals and sentiments are known to forecast equity market volatility (Gupta et al., forthcoming), an interesting analysis for the future would be to investigate the same in our context that spans over a century of data.

References

Ashman, S., Mohamed, S., and Newman, S. (2013). The financialization of the South African economy and its impact on economic growth and employment. UNDESA Discussion Paper. Available at: https://uwe-repository.worktribe.com/output/936659/financialisation-of-the-south-african-economy-impact-on-the-economic-growth-path-and-employment.

Aye G.C., Balcilar, M. and Gupta, R. (2017). International stock return predictability: Is the role of US time-varying? Empirica, 44(1), 121–146.

Aye, G.C., Christou, C., Gil-Alana, L.A., and Gupta, R. (2019). Forecasting the Probability of Recessions in South Africa: the Role of Decomposed Term Spread and Economic Policy Uncertainty. Journal of International Development, 31(1), 101-116.

Aye, G.C., Gadinabokao, O.A., and Gupta, R. (2017b). Does the SARB Respond to Oil Price Movements? Historical Evidence from the Frequency Domain. Energy Sources, Part B: Economics, Planning, and Policy, 12(1), 40-46.

Aye, G.C., Gupta, R., Kaninda, A., Nyakabawo, W., and Razak, A. (2013a). House Price, Stock Price and Consumption in South Africa: A Structural VAR Approach. Corporate Ownership and Control, 10(2), 585-589.

Aye, G.C., Gupta, R., and Modise, M.P. (2013b). Structural Breaks and Predictive Regressions Models of South African Equity Premium. Frontiers in Finance and Economics, 10(1), 49-86.

Aye, G.C., Gupta, R., and Modise, M.P. (2015). Do Stock Prices Impact Consumption and Interest Rate in South Africa? Evidence from a Time-Varying Vector Autoregressive Model. Journal of Emerging Market Finance, 14(2), 1-21.

Balcilar, M., Gupta, R., and Kyei, C. (2018b). Predicting Stock Returns and Volatility with Investor Sentiment Indices: A Reconsideration Using a Nonparametric Causality-In-Quantiles Test. Bulletin of Economic Research, 70(1), 74-87.

Balcilar, M., Uwilingiye, J., and Gupta, R. (2018a). Dynamic Relationship between Oil Price and Inflation in South Africa. Journal of Developing Areas, 52(2), 73-95.

Balcilar, M., van Eyden, R., Uwilingiye, J., and Gupta, R. (2017). The Impact of Oil Price on South African GDP Growth: A Bayesian Markov Switching-VAR Analysis. African Development Review, 29(2), 319-336.

Bannigidadmath, D., and Narayan, P.K. (2015). Stock return predictability and determinants of predictability and profits. Emerging Markets Review, 26, 153–173.

Boubaker, H., Cunado, J., Gil-Alana, L.A. and Gupta, R. (2020). Global crises and gold as a safe haven: Evidence from over seven and a half centuries of data. Physica A: Statistical Mechanics and its Applications, 540(C), 123093.

Bouri, E., Demirer, R., Gupta, R., and Sun, X. (2020). The Predictability of Stock Market Volatility in Emerging Economies: Relative Roles of Local, Regional and Global Business Cycles. Journal of Forecasting, 39(6), 957-965.

Cakan, E., Gupta, R. (2017). Does the US. macroeconomic news make the South African stock market riskier? Journal of Developing Areas, 51(4), 17-27.

Campbell, J.Y. (2008) Viewpoint: estimating the equity premium, Canadian Journal of Economics, 41, 1–21.

Chisadza, C., Dlamini, J., Gupta, R., and Modise, M.P. (2016). The Impact of Oil Shocks on the South African Economy. Energy Sources, Part B: Economics, Planning, and Policy, 11(8), 739-745.

Christou, C., and Gupta, R. (2020). Forecasting equity premium in a panel of OECD countries: The role of economic policy uncertainty. The Quarterly Review of Economics and Finance, 76(C), 243-248.

Christou, C., Gupta, R., and Jawadi, F. (2021). Does Inequality Help in Forecasting Equity Premium in a Panel of G7 Countries? The North American Journal of Economics and Finance, 57, 101456.

Dalika, N., and Yahir Seetharam, Y. (2015). Sentiment and returns: an analysis of investor sentiment in the South African market, Investment Management and Financial Innovations, 12(1), 267-276.

Diebold, F.X., and Mariano, R.S. (1995). Comparing Predictive Accuracy. Journal of Business and Economic Statistics, 13, 253–263.

Degiannakis, S., Filis, G., and Arora, V. (2018). Oil Prices and Stock Markets: A Review of the Theory and Empirical Evidence. The Energy Journal, 39(5), 85-130.

Gebka, B. (2014) The Non-Linear and Linear Impact of Investor Sentiment on Stock Returns: An Empirical Analysis of the US Market. In: Ma, J., Wohar, M, ed. Recent Advances in Estimating Nonlinear Models: With Applications In Economics and Finance, 281-299.

Guidolin, M., Hyde, S., McMillan, D., and Ono, S. (2009). Non-linear predictability in stock and bond returns: When and where is it exploitable? International Journal of Forecasting, 25(2), 373-399.

Gupta, R., and Hartley, F. (2013). The role of asset prices in forecasting inflation and output in South Africa. Journal of Emerging Market Finance, 12(3), 239–291.

Gupta, R., Huber, F., and Piribauer, P. (2020). Predicting international equity returns: Evidence from time-varying parameter vector autoregressive models. International Review of Financial Analysis, 68(C), 101456.

Gupta, R., Majumdar, A., and Wohar M.E. (2017). The Role of Current Account Balance in Forecasting the US Equity Premium: Evidence from a Quantile Predictive Regression Approach. Open Economies Review, 28(2), 47–59.

Gupta, R., and Modise, M.P. (2012a). South African Stock Return Predictability in the Context of Data Mining: The Role of Financial Variables and International Stock Returns. Economic Modelling, 29(3), 908-916.)

Gupta, R., and Modise, M.P. (2012b). Valuation Ratios and Stock Price Predictability in South Africa: Is it there? Emerging Markets Finance and Trade, 48(1), 70-82.

Gupta, R., and Modise, M.P. (2013a). Macroeconomic Variables and South African Stock Return Predictability. Economic Modelling, 30(1), 612-622.

Gupta, R., and Modise, M.P. (2013b). Does the Source of Oil Price Shocks Matter for South African Stock Returns? A Structural VAR Approach. Energy Economics, 40, 825-831.

Gupta, R., Modise, M.P., and Uwilingiye, J. (2016). Out-of-Sample Equity Premium Predictability in South Africa: Evidence from a Large Number of Predictors. Emerging Markets Finance and Trade, 52(8), 1935-1955.

Gupta, R., Mwamba, J.W.M., and Wohar, M.E. (2018). The role of partisan conflict in forecasting the US equity premium: A nonparametric approach. Finance Research Letters, 25, 131-136.

Gupta, R., Nel, J., and Pierdzioch, C. (Forthcoming). Investor Confidence and Forecastability of US Stock Market Realized Volatility: Evidence from Machine Learning. Journal of Behavioral Finance.

Gupta, R., Pierdzioch, C., Vivian, A.J., and Wohar, M.E. (2019). The predictive value of inequality measures for stock returns: An analysis of long-span UK data using quantile random forests. Finance Research Letters, 29(C), 315-322.

Huang, D., and Kilic, M. (2019). Gold, platinum, and expected stock returns. Journal of Financial Economics, 132(3), 50-75.

Jordan S.J., Vivian, A.J., and Wohar, M.E. (2017). Forecasting market returns: bagging or combining? International Journal of Forecasting, 33(1), 102–120

Jordan S.J., Vivian, A.J., and Wohar, M.E. (2018). Stock returns forecasting with metals: sentiment vs. fundamentals. The European Journal of Finance, 24(6), 458-477.
Mensi, W., Hammoudeh, S., Reboredo, J.C., and Nguyen, D.K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. Emerging Markets Review, 19(C), 1-17.
Mensi, W., Hammoudeh, S., Yoon, S-M., and Nguyen, D.K. (2016). Asymmetric Linkages between BRICS Stock Returns and Country Risk Ratings: Evidence from Dynamic Panel Threshold Models. Review of International Economics, 24(1), 1–19.
Naik, P.K., Gupta, R., and Padhi, P. (2018). The Relationship Between Stock Market Volatility And Trading Volume: Evidence From South Africa. Journal of Developing Areas, 52(1), 99-114.
Narayan, P. K., and Gupta, R. (2015). Has oil price predicted stock returns for over a century? Energy Economics, 48, 18–23.
Narayan, P.K, Phan, D.H.B., Sharma, S.S. (2018). Does Islamic stock sensitivity to oil prices have economic significance? Pacific Basin Finance Journal, 53, 497–512.
Phan, D.H.B., Sharma, S.S., and Narayan, P.K. (2015). Stock return forecasting: some new evidence. International Review of Financial Analysis, 40, 38–51.
Phan, D.H.B., Sharma, S.S., and Tran, V.T. (2018). Can economic policy uncertainty predict stock returns? Global evidence. Journal of International Financial Markets, Institutions and Money, 55(C), 134-150.
Rapach, D. E., and Zhou, G. (2013). Forecasting stock returns. Handbook of Economic Forecasting, 2 (Part A), Graham Elliott and Allan Timmermann (Eds.), Amsterdam: Elsevier, 328−383.
Rupande, L., Muguto, H.T., and Muzindutsi, P-F. (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. Cogent Economics & Finance, 7(1), 1600233.
Salisu, A.A., Ademuyiwa, I. and Isah, K. (2018a). Revisiting the forecasting accuracy of Phillips curve: the role of oil price. Energy Economics, 70, 334–356.
Salisu, A.A., Ademuyiwa, I. and Isah, K. (2018b). Predicting US Inflation: Evidence from a new approach. Economic Modelling, 71(C), 134-158.
Salisu, A.A., Cunado, J., Isah, K., and Gupta, R. (2021). Oil Price and Exchange Rate Behaviour of the BRICS. Emerging Markets Finance and Trade, 57(7), 242-2051.
Salisu, A.A., and Gupta, R. (2021). Oil Shocks and Stock Market Volatility of the BRICS: A GARCH-MIDAS Approach. Global Finance Journal, 48(1), 100546.
Salisu, A.A., Swaray, R. and Adediran, I. (2019a). Can urban coffee help predict US inflation. Journal of Forecasting, 38(7), 649-668.
Salisu, A.A., Swaray, R., Oloko, T.F. (2019b). Improving the predictability of the oil–US stock nexus: The role of macroeconomic variables. Economic Modelling, 76, 153-171.
Salisu, A.A., Raheem, I.D. and Ndako, U.D. (2019c). A sectoral analysis of asymmetric nexus between oil price and stock returns. International Review of Economics and Finance, 61, 241-259.
Salisu, A.A., Adekunle, W., Alimi, W.A. and Emmanuel, Z. (2019d). Predicting exchange rate with commodity prices: New evidence from Westerlund and Narayan (2015) estimator with structural breaks and asymmetries. Resources Policy, 62, 33-56.
Salisu, A.A., Swaray, R. and Sa'id, H. (2021). Improving the forecasting accuracy of Phillips curve: The role of commodity prices. International Journal of Finance and Economics, 26(2), 2946-2975.
Salisu, A. A. and Isah, Kazeem O. (2017). Revisiting the oil price and stock market nexus: A nonlinear Panel ARDL approach. Economic Modelling, 66(C), 258-271.

Shin, Y., Yu, B., and Greenwood-Nimmo, M. (2014). Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. In: Sickles R., Horrace W. (eds) Festschrift in Honor of Peter Schmidt. Springer, New York, NY.

Smyth, R., and Narayan, P.K. (2018). What do we know about oil prices and stock returns? International Review of Financial Analysis, 57, 148-156.

Solanki, K., and Seetharam, Y. (2014). Is Consumer Confidence an Indicator of JSE Performance? Contemporary Economics, 8(3), 257-274.

Sousa R.M., Vivian, A., and Wohar, M.E. (2016). Predicting asset returns in the BRICS: The role of macroeconomic and fundamental predictors. International Review of Economics & Finance, 41, 122–143

Tule, M., Salisu, A.A. and Chiemeke, C. (2019). Can agricultural commodity prices predict Nigeria's inflation? Journal of Commodity Markets, 16, 100087.

Tule, M., Salisu, A.A. and Chiemeke, C. (2020). Improving Nigeria's inflation forecast with oil price: The role of estimators. Journal of Quantitative Economics, 18(1), 2020, 191-229.

Wen, Y-C., Lin, P.T., and Roca, E. (2015). Stock return predictability in South Africa: The role of major developed markets. Finance Research Letters, 15, 257-265.

Westerlund, J., and Narayan, P.K. (2012). Does the choice of estimator matter when forecasting returns? Journal of Banking & Finance, 36, 2632–2640.

Westerlund, J., and Narayan, P.K. (2015). Testing for predictability in conditionally heteroscedastic stock returns. Journal of Financial Econometrics, 13, 342–37.

Table 1: Summary and Preliminary Analysis Results

	Mean	Std. Dev.	Skewness	Kurtosis	N	ADF	$ARCH(3)$	$ARCH(6)$	$ARCH(12)$	$Q(3)$	$Q(6)$	$Q(12)$	$Q^2(3)$	$Q^2(6)$	$Q^2(12)$	Persistence
Logged Series																
Gold	2.745	0.239	0.580	2.315	1275	-2.303^{b}	1.456	0.982	1.045	16.094^{***}	17.501^{***}	46.556^{***}	0.279	0.483	1.009	0.996^{***}
Silver	1.068	0.215	1.007	4.088	1275	-2.913^{b}	63.123^{***}	35.790^{***}	19.373^{***}	4.107	6.341	19.522^{*}	177.880^{***}	264.660^{***}	311.010^{***}	0.990^{***}
WTI	1.219	0.201	0.466	2.387	1275	-3.458^{**b}	259.210^{***}	129.509^{***}	64.414^{***}	149.24^{***}	162.330^{***}	169.93^{***}	621.290^{***}	632.810^{***}	644.120^{***}	0.989^{***}
Palladium	2.187	0.269	0.777	3.017	639	-2.393^{b}	16.571^{***}	8.526^{***}	4.813^{***}	20.928^{***}	25.070^{***}	33.392^{***}	63.795^{***}	75.522^{***}	87.585^{***}	0.996^{***}
Platinum	2.505	0.283	-0.340	2.311	639	-1.321^{a}	9.098^{***}	5.451^{***}	2.934^{***}	3.293	8.065	16.179	32.326^{***}	41.271^{***}	49.168^{***}	0.994^{***}
Returns																
South Africa	0.090	5.905	-0.065	6.134	1275	-28.118^{***b}	11.978^{***}	14.461^{***}	9.306^{***}	2.818	10.359	29.472^{***}	40.271^{***}	119.15^{***}	212.97^{***}	0.231^{***}
India	-0.116	6.260	-1.119	16.195	1208	-28.617^{***b}	1.969	1.053	0.805	2.178	9.536	10.876	6.152	6.626	10.604	0.193^{***}
UK	0.045	5.087	-0.185	9.201	1275	-33.735^{***a}	20.801^{***}	12.100^{***}	11.439^{***}	2.510	8.013	11.278	73.802^{***}	104.63^{***}	215.89^{***}	0.056^{**}
US	0.236	4.392	-0.447	14.528	1275	-23.451^{***b}	11.018^{***}	24.546^{***}	16.460^{***}	12.714^{***}	19.799^{***}	22.127^{**}	37.388^{***}	168.510^{***}	281.460^{***}	0.275^{***}

Note: *** and ** denote statistical significance at 1% and 5% respectively. The superscripted "a" and "b" indicate that the augmented Dickey Fuller [ADF] unit root testing framework is based on model with constant only and model with constant and trend, respectively. Std. Dev. is the standard deviation. The Q(k) and Q^2(k) statistics are obtained from the Ljung-Box test for serial correlation respectively using the residuals and squared residuals of the test regressions where k=3,6,12. The ARCH (k) reports the F-statistics of the ARCH-LM test used to test for conditional heteroskedasticity. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM (F distributed) test is that there is no conditional heteroscedasticity.

Table 2: Diebold and Mariano (DM, 1995) Test Results (Predictive Model versus *AR(p)* Model)

		Aggregate				**Negative**				**Positive**			
		South Africa	**India**	**UK**	**US**	**South Africa**	**India**	**UK**	**US**	**South Africa**	**India**	**UK**	**US**
75:25 Split													
Comparison with benchmark model													
Gold	$h=3$	-6.94***	6.43	-5.20***	-69.04***	-47.96***	28.03	-2.30**	-51.96***	-7.11***	16.96	-2.62***	-33.45***
	$h=6$	-7.00***	6.41	-5.27***	-69.13***	-47.76***	28.11	-2.38***	-52.14***	-7.10***	16.74	-2.83***	-33.55***
	$h=12$	-7.08***	6.29	-5.43***	-69.30***	-47.42***	28.12	-2.56***	-52.50***	-7.02***	16.19	-3.25***	-33.81***
Silver	$h=3$	-5.47***	61.75	6.16	-28.96***	-4.47***	47.37	-3.37***	-150.53***	-7.25***	31.75	-3.14***	-77.31***
	$h=6$	-5.46***	61.96	6.21	-29.06***	-4.50***	46.84	-3.54***	-150.99***	-7.24***	31.39	-3.32***	-77.53***
	$h=12$	-5.35***	62.36	6.34	-29.26***	-4.47***	45.83	-3.91***	-151.55***	-7.19***	30.61	-3.68***	-77.94***
WTI	$h=3$	-6.99***	18.04	6.44	-32.69***	-13.74***	47.19	-1.37*	-48.54***	-8.98***	33.71	-12.71***	-291.14***
	$h=6$	-6.97***	18.14	6.5	-32.81***	-13.63***	46.7	-1.53*	-48.64***	-8.97***	33.25	-12.87***	-291.62***
	$h=12$	-6.90***	18.3	6.64	-33.07***	-13.36***	45.58	-1.83**	-48.91***	-8.88***	32.28	-13.18***	-293.05***
Comparison with sentiments with fundamental													
Gold	$h=3$	-2.93***	-8.87***	-10.78***	-7.37***	-11.59***	1.02	-2.02**	5.84	-3.90***	-9.40***	4.01	1.17
	$h=6$	-3.00***	-8.99***	-10.88***	-7.30***	-11.65***	1.15	-2.06**	5.86	-3.89***	-9.45***	3.82	1.15
	$h=12$	-3.11***	-9.23***	-11.13***	-7.11***	-11.80***	1.33	-2.15**	5.89	-3.85***	-9.61***	3.41	1.09
Silver	$h=3$	-1.58*	12.16	0.56	-8.51***	2.25	-0.46	-3.28***	2.6	-1.84**	-6.73***	2.28	-7.34***
	$h=6$	-1.58*	12.17	0.55	-8.54***	2.18	-0.47	-3.41***	2.64	-1.83**	-6.67***	2.12	-7.37***
	$h=12$	-1.51*	12.2	0.57	-8.55***	2.12	-0.42	-3.71***	2.72	-1.83**	-6.57***	1.8	-7.39***
25:75 Split													
Comparison with benchmark model													
Gold	$h=3$	-57.46***	2.83	16.15	-24.81***	-5.76***	2.37	12.56	-48.86***	-19.21***	-0.42	10.91	-29.96***
	$h=6$	-58.03***	2.79	16.26	-25.07***	-5.91***	1.98	12.76	-48.97***	-19.46***	-0.56	11.15	-30.19***
	$h=12$	-59.18***	2.73	16.5	-25.61***	-6.21***	1.32	13.2	-49.16***	-19.94***	-0.86	11.62	-30.67***
Silver	$h=3$	-1.06	4.22	11.34	-22.77***	-19.33***	4.23	7.52	-24.84***	-5.06***	4.26	13.71	-28.80***
	$h=6$	-0.86	4.22	11.58	-23.04***	-19.45***	3.98	7.74	-25.09***	-4.85***	3.98	13.95	-29.13***
	$h=12$	-0.45	4.47	12.05	-23.57***	-19.70***	3.49	8.2	-25.59***	-4.51***	3.25	14.43	-29.64***
WTI	$h=3$	-5.45***	9.6	4.16	-10.39***	-11.58***	5.35	12.63	-23.10***	-14.50***	3.85	11.19	-22.55***
	$h=6$	-5.46***	9.53	4.23	-10.53***	-11.62***	5.17	12.87	-23.33***	-14.46***	3.63	11.43	-22.81***
	$h=12$	-5.47***	9.38	4.42	-10.82***	-11.70***	4.81	13.34	-23.79***	-14.67***	3.22	11.9	-23.36***
Comparison with sentiments with fundamental													
Gold	$h=3$	-2.69***	-3.96***	0.94	1.01	-0.88	-6.31***	-3.96***	-3.67***	-2.00**	-5.16***	-2.60***	7.12
	$h=6$	-2.77***	-3.97***	0.9	1.04	-1.04	-6.54***	-4.23***	-3.49***	-2.16**	-5.16***	-2.72***	7.24
	$h=12$	-2.92***	-3.97***	0.78	1.11	-1.31*	-6.95***	-4.71***	-3.16***	-2.34***	-5.19***	-2.80***	7.27
Silver	$h=3$	6.22	-2.36***	2.37	-3.74***	-6.28***	-2.60***	-4.40***	-6.22***	11.06	-0.63	-8.87***	2.25
	$h=6$	6.34	-2.33**	2.48	-3.86***	-6.34***	-2.76***	-4.43***	-6.26***	11.17	-0.68	-9.10***	2.36
	$h=12$	6.59	-1.85**	2.71	-4.10***	-6.47***	-3.06***	-4.49***	-6.36***	11.54	-1.06	-9.53***	2.34

Note: Comparing predictive model against an autoregressive model, such that significantly negative DM statistic implies better forecast performance of the predictive model over the autoregressive model, while in the case of the comparison between our predictive model with sentiments versus fundamental, significantly negative DM statistics implies better performance of model with sentiments over model with fundamental. ***, ** and * denote 1%, 5% and 10% level of significance with critical values of 2.33, 1.65 and 1.28 respectively, respectively.

Table 3: Diebold and Mariano (DM, 1995) Test Results (Predictive Model versus *AR(p)* Model): South Africa

			Aggregate		Negative		Positive	
			75:25 Split	**50:50 Split**	**75:25 Split**	**50:50 Split**	**75:25 Split**	**50:50 Split**
Comparison with benchmark model								
Palladium		$h=3$	-15.90***	-6.06***	-11.57***	-15.08***	-19.77***	-7.05***
		$h=6$	-15.89***	-6.12***	-11.54***	-15.23***	-19.63***	-6.98***
		$h=12$	-15.53***	-6.23***	-10.69***	-15.42***	-19.90***	-6.91***
Platinum		$h=3$	-53.34***	-18.77***	-132.38***	-29.01***	-42.89***	-12.56***
		$h=6$	-53.53***	-18.87***	-132.93***	-29.00***	-43.01***	-12.50***
		$h=12$	-53.82***	-18.99***	-134.32***	-28.66***	-43.20***	-12.52***
Comparison with Gold, Silver and WTI								
Gold	Palladium	$h=3$	2.24	1.05	3.62	3.32	3.22	0.99
		$h=6$	2.36	1.02	3.64	3.31	3.35	0.92
		$h=12$	2.44	1.29	3.6	3.57	3.54	1.12
	Platinum	$h=3$	1.85	0.97	7.93	1.45	3.51	2.77
		$h=6$	1.92	0.93	7.99	1.4	3.55	2.71
		$h=12$	2.16	1.17	8.14	1.62	3.71	2.95
Silver	Palladium	$h=3$	2.27	0.98	5.38	3.34	4.81	1.01
		$h=6$	2.39	0.95	5.39	3.32	4.95	0.94
		$h=12$	2.47	1.22	5.34	3.59	5.13	1.14
	Platinum	$h=3$	1.81	0.91	9.56	1.46	5.08	2.79
		$h=6$	1.88	0.87	9.61	1.41	5.12	2.72
		$h=12$	2.13	1.11	9.75	1.63	5.27	2.96
WTI	Palladium	$h=3$	4.51	1.11	5.04	3.33	6.75	0.99
		$h=6$	4.62	1.08	5.05	3.32	6.88	0.92
		$h=12$	4.68	1.35	5.01	3.58	7.04	1.12
	Platinum	$h=3$	4.19	1.03	9.39	1.45	7.08	2.77
		$h=6$	4.26	0.99	9.44	1.41	7.12	2.7
		$h=12$	4.48	1.23	9.58	1.62	7.24	2.95

Note: Comparing predictive model against an autoregressive model, such that significantly negative DM statistic implies better forecast performance of the predictive model over the autoregressive model, while in the case of the comparison between our predictive model with Gold, Silver and WTI versus sentiments (palladium and Platinum), significantly negative DM statistics implies better performance of model with Gold or Silver or WTI over model with either palladium or platinum. ***, ** and * denote 1%, 5% and 10% level of significance with critical values of 2.33, 1.65 and 1.28 respectively.