North American Journal of Economics and Finance 35 (2016) 38–55

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

A quantile-boosting approach to forecasting gold returns

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ARTICLE INFO

Article history:
Received 3 July 2015
Received in revised form 25 October 2015
Accepted 26 October 2015
Available online 10 November 2015

Keywords:
Quantile-boosting approach
Forecasting
Asymmetric loss
Gold returns

ABSTRACT

We use a quantile-boosting approach to compute out-of-sample forecasts of gold returns. The approach accounts for model uncertainty and model instability, and it allows forecasts to be computed under asymmetric loss functions. Different asymmetric loss functions represent different types of investors (optimists versus pessimists). We document how the performance of a simple trading rule varies across investor types.

1. Introduction

Against the background of recent financial crises and market jitters, much significant research has been done to recover the major macroeconomic and financial determinants of gold returns. We reexamine the forecasting power of several determinants of gold returns using a quantile-boosting approach. The quantile-boosting approach combines the advantages of quantile-regression techniques and boosting techniques. Boosting techniques, the first main element of the quantile-boosting approach, make it possible to efficiently build a forecasting model when economic theory implies that several potential predictors should be taken into account. In the case of gold, researchers have considered several competing predictors because no consensus has emerged as to which are the core

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http://dx.doi.org/10.1016/j.najef.2015.10.015
1062-9408/

determinants of gold returns. Among the predictors that researchers have studied are the inflation rate (Beckmann & Czudaj, 2013; Shahbaz, Tahir, Ali, & Rehman, 2014), the oil price (Reboredo, 2013), the exchange rate (Pukthuanthong & Roll, 2011), business-cycle fluctuations (Pierdzioch, Risse, & Rohloff, 2014b), and stock returns (Beckmann, Berger, & Czudaj, 2015). Because not all potential predictors may have predictive power for gold returns at all time, the boosting approach starts with a parsimonious forecasting model that is then transformed into a more complex model using a computationally efficient step-by-step algorithm. The list of recent applications of boosting techniques in economics includes the research by Berge (2013), Wohlrabe and Buchen (2014), and Pierdzioch, Risse, and Rohloff (2015a, 2015c). The latter apply boosting techniques to study gold returns, but not in the context of a quantile-regression approach, that is, they do not consider the possibility that an investor has an asymmetric loss function.

The second main element of the quantile-boosting approach are quantile-regression techniques. In recent years, researchers have successfully applied quantile-regression techniques in various contexts in the empirical finance and forecasting literature (Baur, Dimpfl, & Jung, 2012; Meligkotsidou, Vrontos, & Vrontos, 2014; Pedersen, 2015). Quantile-regression techniques also have been used to study several important aspects of gold-price fluctuations (Baur, 2013; Dee, Li, & Zheng, 2013; Ma & Patterson, 2013; Zagaglia & Marzo, 2013). In a forecasting context, Pierdzioch, Risse, and Rohloff (2015b) use quantile-regressions to study the statistical accuracy of out-of-sample forecasts of gold returns. Quantile-regression techniques, however, have not been studied in the gold-price literature in combination with a boosting approach as the integration of quantile regressions and boosting is a recent development (Fenske, Kneib, & Hothorn, 2011; Yuan, 2015; Zheng, 2012; for a least-absolute error boosting approach, see Friedman, 2001). Quantile-regression techniques have the advantage that they render it possible to compute forecasts that target the conditional quantiles of the distribution of gold returns. Targeting the conditional quantiles of the distribution of gold returns rather than its conditional mean is advantageous if an investor has an asymmetric loss function. An asymmetric loss function may reflect forecaster's optimism or pessimism, other behavioral biases, or it may arise in a risk-management context when a forecast is being used to monitor a position in options or other financial derivatives with an asymmetric payoff function.

We use a quantile-boosting approach to compute out-of-sample forecasts of gold returns. We then use the forecasts to study whether an investor can use the forecasts to set up a profitable trading rule. In order to make sure that our results can be directly compared with results reported in earlier research, we study, like Pierdzioch et al. (2014a, 2014b), a trading rule that requires switching between an investment in a riskless asset and an investment in gold. Importantly, because investors with different asymmetric loss functions (we call them optimists and pessimists) will base their investment decisions on different quantile forecasts, we study how different types of investors would benefit from following the simple trading rule (for heterogeneous-agent models of commodity markets, see Baur & Glover, 2014; Reitz, Rülke, & Stadtmann, 2012; Reitz & Slopek, 2010). Upon comparing the performance of our simple trading rule with the performance of a buy-and-hold strategy, we document that an investor with a symmetric loss function, after factoring in transaction costs, would have earned a lower terminal wealth and a lower Sharpe's ratio than a passive buy-and-hold investor. When we consider an optimistic investor, in contrast, our trading rule often performs better than a buy-and-hold strategy. Not surprisingly, an optimist would have benefited to a larger extent from the run up of the gold price that occurred after 2002 than an investor with a symmetric loss function or a pessimist. However, we also show that the link between performance and investor optimism is nonlinear, and that being too optimistic does not pay off. Furthermore, we show that an investor whose loss function changes its shape according to market conditions would not have performed systematically better than an investor with a time-invariant shape of the loss function. Using a recursive-estimation window to setup the quantile-boosting approach results in a better performance than using a relatively short rolling-estimation window. Finally, we compare the performance of the quantile-boosting approach with the performance of the widely-studied lasso quantile-regression approach.

We proceed as follows. In Section 2, we sketch the quantile-boosting approach. In Section 3, we describe our data and we summarize our empirical results. In Section 4, we conclude.