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Googling gold and mining bad news

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ABSTRACT

This paper studies investor's attention to gold price movements by analyzing the relationship between gold price changes and internet search queries for gold. We find a positive relationship of gold price volatility and search queries and a strong asymmetric effect of negative gold price changes on search queries indicating a preference to mine (google) bad news rather than good news. The analysis of silver, palladium and platinum demonstrates that the findings for gold are unique.

To gold they tend, On gold depend, All things! (Goethe, Faust I, verses 2802ff).

1. Introduction

There is a growing literature on internet search queries, investor's attention, and sentiment. In their ground-breaking article, Choi and Varian (2012) use Google search queries (SQs) to predict different economic indicators. Da et al. (2011) show that the volume of Google search queries serves as a direct measure of retail investor attention towards individual stocks. Stocks which receive high attention in the current week outperform other stocks by approximately 30 basis points in the following two weeks. Similarly, Drake et al. (2012) use Google SQs as a way to approximate demand for (public) information around earnings announcements. Building on these findings, Vlastakis and Markello (2012) and Dimpfl and Jank (2016) investigate the relationship between stock market volatility and Google search queries. They find that incorporating SQs in the prediction significantly improves the forecasting accuracy, a result which is well in line with the theoretical information demand model of Andrei and Hasler (2016). Recently, Da et al. (2015) proposed an aggregate index of Google search queries called "FEARS" index to measure investor sentiment. The authors show that this index is able to explain contemporary mispricing of stocks, volatility of stock prices, and the transfer of wealth from mutual funds to bond funds. Their results are fully consistent with the theory about investor sentiment in financial markets (see De Long et al. (1990)).

Despite the growing literature which seeks to grasp the impact of investor attention, studies on commodities and in particular precious metals are still rare. In this article, we use the by now well established methodology to map investor attention to precious metals. In particular, we follow Da et al. (2011) and Bank et al. (2011) and interpret Google search queries as a measure for retail investors' attention and assume that large asset price changes induce an elevated interest of retail investors.

The focus of this paper lies on precious metals and in particular on gold. Since gold has a long tradition as a currency, a medium of exchange and a store of value, it is possible that investors behave differently with respect to gold than to silver, palladium, and platinum. Gold's high value density, its bright and shiny reflection may further influence investors' emotions, behavior and attention and we expect that the attention is different for gold than for the other precious metals. Hence, we aim to analyze the question if retail investors react to price changes by using Google and thus by mining information about the asset. Furthermore, we are interested in the question whether information generation (e.g. through googling) and possible subsequent trading of noise traders increases the volatility of the related asset as suggested by, amongst others, Black (1986) or Shleifer and Summers (1990). A first glance at Fig. 1 supports this notion: the spikes in search volume very much coincide with large price changes (up or down).

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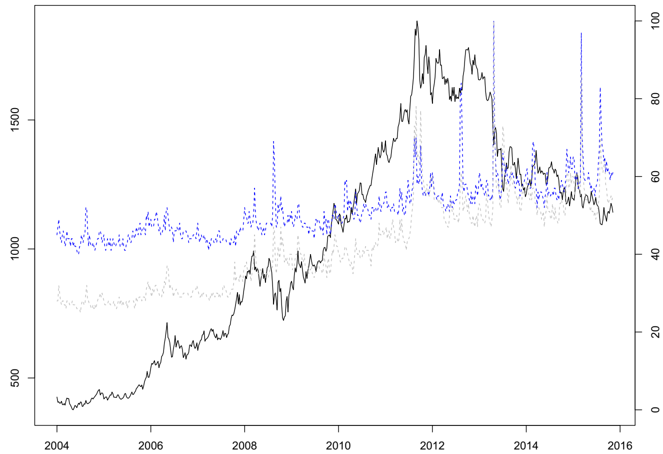

Fig. 1. Gold Time Series. The graphic presents time series plots for the prices (left axis, black solid line) and the Google search volume index (right axis, dashed lines) for gold. The blue line is the entire search volume associated with the respective search term, the gray line is the volume limited to searches for the chemical element. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

This paper contributes to the growing literature on internet search queries and investor attention with an analysis of precious metals. Using a new filter provided by Google, we are able to concentrate the search queries to searches related to the metals only, leaving aside unrelated searches which might involve the search term, but not be related to the asset's price. The findings of the empirical analysis can be summarized as follows. Lagged and contemporaneous returns and return volatilities influence search queries and the effects are significantly stronger for gold than for silver, palladium and platinum. We also find a strong asymmetric effect between negative gold returns and positive gold returns on changes of search queries for gold. In other words, bad news increase search queries by more than good news. We demonstrate that there is a link between the well-establish asymmetric volatility effect and the asymmetric search query effect.

The remainder of the paper is structured as follows. Section 2 presents the data and the econometric models. Section 3 holds the econometric analysis with the estimation results. Finally, Section 4 summarizes the main findings and provides concluding remarks.

2. Data and methodology

This section establishes the econometric framework for our analysis. We first present the data and subsequently describe the return and volatility models that will be estimated.

2.1. Data

We use Google search query data for gold, silver, palladium, and platinum which are obtained from google.com/trends. Google very recently added the feature to filter the search query with respect to the final objective of the search. In the case of gold (and silver) this is very important as we are interested solely in searches that are related to the precious metal gold, the chemical element, but not in searches for, say, gold as in a gold medal. Based upon which website is accessed after a search for the term “gold”, Google flags the search as related to different categories. These are “general”, i.e. without any limitation, “chemical element”, “color, an award category (containing, for example, the ”Golden Gramophone Award”), and an event category which contains searches related to, for example, the Klondike gold rush (1896–1899) or the California gold rush (1848–1855).

The following example illustrates why the distinction might be important. In August 2008 total search volume for gold increased by 38% from week 32 to week 33 while search volume for the chemical element only increased by 27% (see Fig. 1). Google reports that the spike of the total search volume is to some extent caused by searches intended to find information on Michael Phelps winning eight gold medals during the Olympic games in China between August 9 and August 17. This period, however, may also be considered to pertain to the prologue of the global financial crisis. In our asset pricing context winning a gold medal should by itself not be a driver of the gold price, but information about an upcoming crisis should. Also, if attention is steered towards gold as an investment opportunity in light of the upcoming crisis because Michael Phelps won the gold medals, this should result in information demand about gold and its price, but no longer in searches for gold medals. In our analysis we will therefore rely on searches that are related to the chemical element.

After this initial filtering, it would be possible to apply a second stage filter and obtain only search volume that is related to the category “Finance” or “Investment” which is a subgroup thereof. In our analysis it turns out that this additional restriction does not qualitatively alter our results. We therefore resort to only using the first stage filtering to “chemical element”.

The data for the spot prices of gold, silver, palladium, and platinum are obtained from Thomson Reuters Datastream and denoted in US dollar.[1] The time span and the data frequency is determined by the Google data. As Google only provides an index which is standardized with respect to the highest number of searches of any day during the desired time period, we need to download the complete dataset as a whole. The consistency of the dataset, however, comes at the cost that these data are only provided on a weekly frequency. Daily data can only be downloaded for one year and the individual scaling prevents us from stringing them together. Hence, our sample consists of weekly data from January 2004 until November 2015.[2] The time series of Google search volumes and prices of gold have already been shown in Fig. 1. The remaining time series of silver, palladium, and platinum are presented in Fig. 2. The statistical properties of the precious metal returns display the well-known features such as significant skewness and excess-kurtosis.

The data are checked for stationarity using an Augmented Dickey-Fuller test with automatic lag length selection based on the BIC. Table 1 contains the test results. As can be seen, all price series are non-stationary. The search queries are also predominantly non-stationary. Only the platinum time series might be considered stationary, depending on the significance level chosen. This is no real issue as we use log-changes for all variables in the subsequent analysis. As can be seen from columns 4 and 5 of Table 1, the log-changes are all found to be stationary. We also analyzed whether google search queries for a certain precious metal and the respective prices would be cointegrated (using the Engle-Granger methodology), but found no empirical support for this hypothesis.

2.2. Econometric models

We analyze both return and volatility dynamics in univariate, autoregressive models. We use three sets of models to analyze (i) the relationship of returns with SQ changes, (ii) the relationship of return volatility with SQ changes and (iii) the relationship of return volatility with the volatility of SQ changes.

[1] The gold prices are London Bullion Market US dollar prices per troy ounce of gold, the silver prices are Handy & Harman Base US dollar prices per troy ounce of silver and the palladium and platinum prices are London Metals Exchange US dollar prices per troy ounce.

[2] The data have been downloaded in November 2015. Google continuously updates and cleans the search volume data which leads to differences in search query time series when downloading them again at a later stage. We therefore repeated the analysis on a subsample of 5 years (when revising the article in 2016 weekly data are only provided for a time span up to 5 years) using both the original download and a newly downloaded dataset. We find the time series to be highly correlated (above 0.95) and the results are not altered by using the new dataset.