Contribution of the Bitcoin to the Modelling and Forecasting of Gold Prices

Bachelor Thesis
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Abstract

In this paper, gold and Bitcoin returns are investigated for correlation in the concurrent and lagged relationships. Models using bitcoin returns as an exogenous variable (ARIMA transfer, Distributed Lag) as well as an endogenous variable (VAR, VARMA) are used. The logical course of these models is to be understood as an iterative addition of more data, and are then tested for predictive power and compared to a benchmark. This was carried out in order to acquire a statistical understanding of the Bitcoin data as compared to other financial instruments, and thus contribute to the process of developing a better understanding of it. It was found that a structural break took place as the Bitcoin started to be perceived as a tradable asset, significantly changing the relationship between the two series. Further, it was shown that models that include the Bitcoin as an exogenous variable beat the benchmark when it comes to predictive power. These findings are important to those who seek to acquire a deeper understanding of the behavior of the Bitcoin, as well as those who are looking for potential omitted variables in gold forecasts.

Acknowledgments

I would like to thank Prof. Dr. Michael Wolf for supervising this thesis.

Contents

1 Introduction

At the time of this writing, numerous financial institutes (most notably global banks), are experimenting with implementing cryptocurrency (which is a fancy word for a digital currency that uses cryptography in it's transactions) into their daily business.The main purpose for doing this is to reduce payment transaction times, due to their detachedness from a centralized monitoring and transferring institution. While these researching institutions are most likely to come up with a tangible asset that is closely regulated inside of their respective businesses, and has a specific functional orientation (i.e. the usage as an alternative form to transfer payments), the concurrent forms of cryptocurrencies, most notably the Bitcoin, do not possess such a degree of specification. Even though it was invented to serve as a substitute for centralized currencies, which are influenced by governmental and monetary policies, and thus depend on exogenous factors to determine their valuation, they have found plenty of other usages, most notably as a tradable asset or a means of payment for illegal activities that demand for a certain degree of intransparency.
This study seeks to contribute to the discussion about the Bitcoin's intrinsic function through the statistical analysis of the correlation with the returns of gold, and the comparison of the found relationship with the results of the extensive research on factors that are correlated with the gold prices. This will allow us to draw inferences about the functionality that the Bitcoin possesses as on the basis of the behavior of its price relative to the price of gold (as opposed to the predominantly qualitative studies that have so far been conducted). The findings will allow us to judge, if, from a statistical point of view, the Bitcoin shows the behavior of assets such as currencies, stocks, or similar. Finally, we will investigate the Bitcoin for any predictive power to forecast the future gold returns. This paper extends the previously made quantitative research by the evaluation of the Bitcoin's linkage to an asset that has been of major importance in the recent history, as opposed the the (scarce) research conducted by directly investigating the relationship between the Bitcoin and other assets such as common stocks.
In the first part we are going to summarize the research that has been conducted in order to assist the classification and perception process surrounding the Bitcoin. Then we are going to point out the relevant asset classes and their respective correlations with the gold price, in order to allow for a later comparison with the relationship between the Bitcoin and the gold returns. In the following chapters, the used data is going to be introduced and statistical

methods are going to be applied in order to investigate the two series for correlation and conclusion about the quantitative classification will be formulated. After, the results of gold return forecasts using Bitcoin data are evaluated for predictive power. In the last part, the results will be discussed.

1.1 Functional classification of the Bitcoin

Very little scientific research has been conducted to increase the understanding about the function of the Bitcoin in everyday usage. Further, most pieces on the subject that are found in popular magazines focus on the Bitcoin's usage as a substitute currency exclusively (Hobson:2013 and Zohar:2015). While this is aligned with the purpose that the Bitcoin was created for, this exclusive classification would require the Bitcoin to share most of the common properties of currencies. However, there are many of this properties that the Bitcoin so far failed to obtain. Most notably, many of the (relevant) currencies show much less volatility with the reason that even though they yield no intrinsic value, they are backed by a sovereign state that, to some extent, will defend its valuation. And even if the volatility is rather high, say, during high inflation, it is a lot more predictable than the Bitcoin movement. The price of the Bitcoin however is subject to the public's trust in it, and is not backed by securities or promises of any kind.

A more thorough approach to help understand the Bitcoin is shown by Yermack (2013). He conducts an analysis of the weaknesses and strengths of the Bitcoin's usage in the respective functions and concludes, that more stability is needed in order for it to become a viable long-term investment choice or substitute for currencies. Another extensive qualitative survey of the historical functions and outlook of the Bitcoin's incorporation into the daily life is shown in Böhme et al. (2015). They state that, in the early days, an exclusive functionality of being a means of payment was observed. Currently, most of its users either acquire it to process customer payments, or buy it and then hold it for a longer time (thus making it a medium term investment choice). He predicts, that a decrease in volatility would lead to increased usage as a currency, and add the possibility to make it a viable store of value (comparable to the common perception about one of the functions of gold).

The, to my best knowledge, only quantitative survey with the purpose of aiding in the classification of the Bitcoin is shown by Baek and Elbeck (2015). They try to answer, through statistical analysis and comparison of volatility and coefficients in linear regression, if the Bitcoin behaves like an investment or rather a speculative vehicle. They show, that none of the macroeconomic factors show correlation in the concurrent movement, and that the volatility in the Bitcoin is much higher than the volatility in a corresponding stock market (as they are comparing to an index of bundled stocks, no inference can be made if the Bitcoin serves as a viable portfolio choice). The paper concludes, that the Bitcoin shows the properties of a speculative vehicle, but states, that if the usage in every-day-life grows, the Bitcoin is likely to become a viable long-term investment (however, no evidence for this claim is shown).

Thus, three major potential functionalities can be specified.

- Its intrinsic function, to become a substitute to the centralized currencies of sovereign states, a globally viable means of payment.
- A long term store of value, comparable to the way gold or silver is commonly perceived. This is intuitively objected by the fact that the Bitcoin yields no intrinsic value.
- A short-term investment, comparable to stocks, that will be acquired and sold for short term speculation profits. This however is again rejected intuitively, since the Bitcoin, unlike stocks or bonds, is not backed by any company and their assets.

I urge the reader to note, that this paper will not state any qualitative arguments towards one of these functionalities, but rather seeks to compare the behaviour in its price with the behavior of prices in assets of the respective functional classes.

1.2 Correlations with the gold price

To keep the task manageable, evidence, direction and magnitude of correlation will be taken from previous research concerned with the modeling and forecasting of gold returns. Selection criteria for the studies used to describe the interdependence of the factors are twofold. First, the frequency has to match, the data set needs to consist of daily values. Second, the period covered has to be similar to the period covered by our studies, as the interdependence of financial assets is assumed to potentially be subject to changes as time progresses.
First we are going to have a look at the relationship between gold returns and

the stock market. An extensive amount of research has been conducted in this area. The for our purposes most important findings are as follows:

- There is no significant short term co-integration between gold and stock returns (Dee et al., 2013 and Hassani et al., 2015).
- In the time of bull markets, where the average stock prices are increasing, there exists a positive relationship (coefficient) between the concurrent returns of the stock market and Gold (Dee et al., 2013 and Baur and Lucey, 2010). As during the whole period covered by our Bitcoin data, the stock market is increasing, the relationship in times of bear markets and market crashes is of less significance for our study.
- The first lag of gold returns is positively correlated with stock market returns (Baur and Lucey, 2010 and Miyazaki and Hamori, 2013). Miyazaki and Hamori (2013) also find a positive relationship of the first lag of the stock market returns and the gold price.

To test for a possible function as a long term investment, we don't have to look too far, as gold is commonly referred to as an asset to turn to, if in search of a long term store of value (e.g. Financial Times: *"Gold regains its glister: In times of turmoil, gold resurfaces as a potential safe haven"*[1]). Similar assets would include other precious metals, such as silver. Pipattadanukul (2012) shows, that there exists co-integration between the gold and silver returns. Further, Batten et al. (2012) show, that there exist strong positive correlations between the returns. A third comparison would be given by commonly proclaimed risk-free assets such as government bonds. In an extensive study, Ciner et al. (2013) show, that bond returns have a significant negative concurrent correlation with gold returns, however this is offset by a positive first order correlation of the same magnitude, thus rendering the bond returns with no significant correlation past the first horizon. On the other hand, the effect of gold on bond returns appears to be negative for both the concurrent and first order returns. No study was found for an evaluation of the co-integration of gold and bond prices. The combination of these studies shows that there is no common structure across the entirety of the commonly proclaimed *long-term-investments* in the short term. However, silver and gold behave in a similar manner, both in the long term and in the short term.

[1] `https://next.ft.com/content/89dcfe34-56bf-11e5-9846-de406ccb37f2`;04.01.2016

As for the behavior of currencies, relative the the returns of gold, we encounter a possible problem. As the Bitcoin, as well as gold, will be denominated in US dollars in our study, we are effectively removing a change in the valuation of the two through a change in the US dollar against other currencies. This effect of the fluctuation of the relative US dollar price, however, is important when comparing to the gold price, denominated in US dollars, directly. Many studies neglect this problem (e.g. Capie:2005) and study the influence of the relative price of US dollars on the price of gold, denominated in USD, thus theoretically biasing the correlation-coefficient, if their inference is concerned with the effect of the relative dollar strength on gold prices. Now, what we are trying to observe, is an effect of insecurity in the currency on the gold prices. Very little research exists that makes inferences while modeling correctly to remove this potential bias. Reboredo (2013), avoids this problem using copulas, and finds, that there is a positive concurrent correlation between gold returns and the depreciation of the USD, holding constant the value of the USD as compared to other important world currencies. This result however is only partially useful for our study, since he was using weekly data. The same approach, using copulas in an attempt to isolate the effect of the US dollar on gold prices, was chosen by Sjaastad (2008). He also finds, that a concurrent positive and significant relationship between gold and the depreciation of the US dollar exists across all evaluated models. The drawback of the usage of this paper is that the used data set covers a significantly different period (1991:2004) than the one evaluated in this study. However, both of the studies using copulas show the same effect, making it more likely that this effect still prevails for our covered period, and frequencies, than not.

2 Data

Our data set consists of the daily values (if observed) for Bitcoin and Gold prices, covering the roughly five years between September 18, 2010, (which is approximately when Bitcoin prices first were recorded) and September 10, 2015.

2.1 Bitcoin

The data series of the Bitcoin[2] is divided into two distinct parts of different origins, the first part consisting of values obtained by the in 2013 defaulting Bitcoin exchange *Mt. Gox*, the second part, starting July 1, 2013, consisting of the closing values as observed by the CoinDesk *Bitcoin Price Index (XBP)*, on the basis of the midpoint of bid/ask spread[3].

Figure 1 shows the plot for the daily values for all of the period covered.

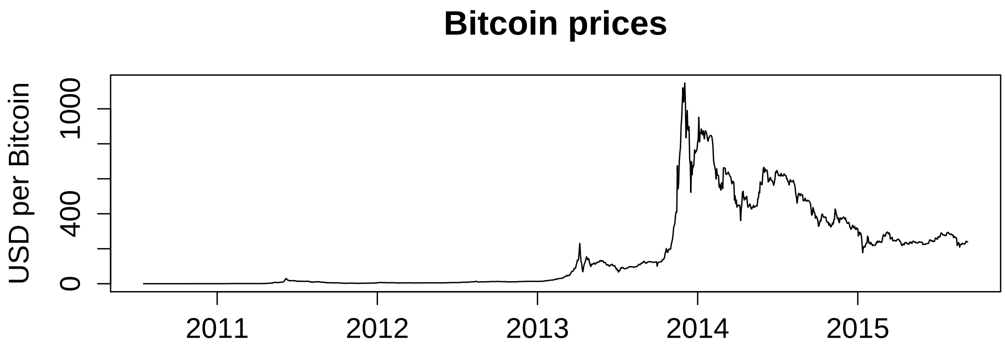

Figure 1: Daily Bitcoin values for every weekday of the covered period

The value is understood as the price of one bitcoin in US Dollar. It is obvious that the time series is non-stationary, further structural changes in the form of bubbles are apparent. The maximum price is attained on December 4, 2013, when it reached 1147 US $ per bitcoin.
Since Bitcoin data is recorded 7 days a week while gold is limited to trading days, only data for the weekdays (while further excluding public holidays) will be used, while creating a dummy variable (which will be explained in section 2.3.1) to preserve any information that is removed by just showing the difference between Friday and Monday.
The time series is non-stationary, most obviously violating the assumption of a time-independent mean, and therefore needs to be adjusted in order to be used in most of the common forecasting techniques (such as ARIMA and VAR).

Figure 2 shows evidence that the first difference of the logarithmized time series approximates stationarity closer then a deterministic trend (which we can therefore rule out, given there also exists no theoretical explanation for a continuous increase or decrease of the Bitcoin price over time).

[2]`http://www.coindesk.com/price/`; 11.09.2015
[3]`http://www.coindesk.com/price/bitcoin-price-index/`; 17.09.2015

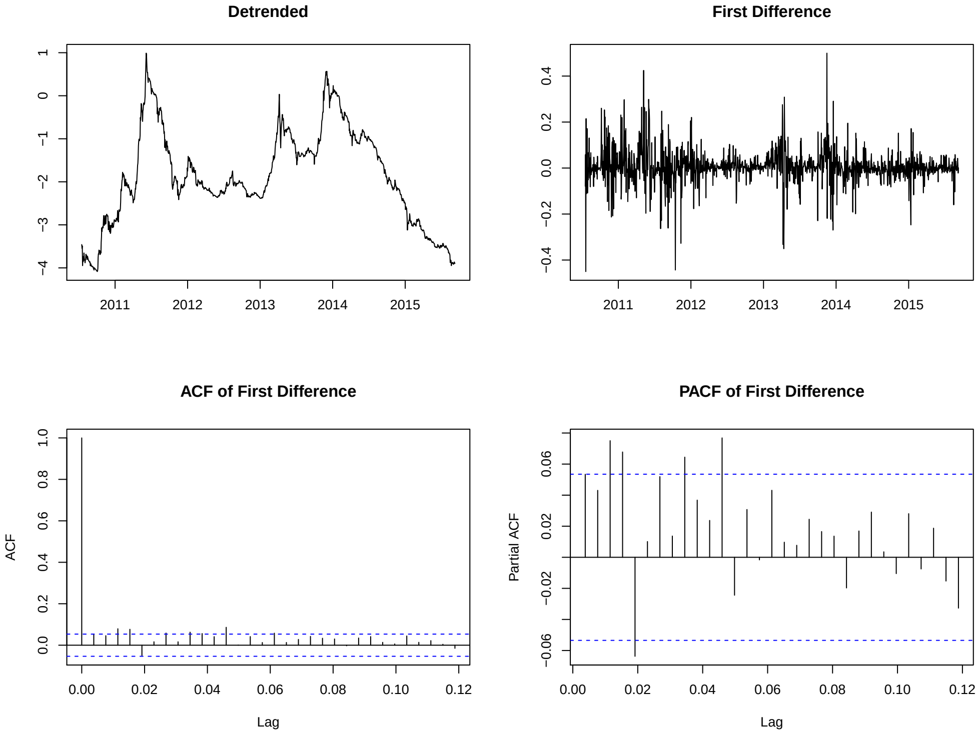

Figure 2: Detrended and first difference of the logarithms of the Bitcoin price. Below the ACF and PACF for the first difference of the series

To put the new series in a financial context, we define the price of one Bitcoin at time t as $Bitcoin_t$, and the return of one Bitcoin at time t as $Bitreturn_t$, where $Bitreturn_t = ln(Bitcoin_t) - ln(Bitcoin_{t-1})$. Further we define the return of a weekday as the difference between the value on that day, and the day before. The return of Monday equals the difference between Friday and Monday. As for the stationarity of the transformed series, we still have autocorrelation (as seen be the ACF and PACF graphs in figure 2), but the series seems to show stationarity. This is also confirmed by the Augmented Dickey-Fuller test, which rejects the null-hypothesis of a unit root in the $Bitreturn$-series on the 99%-level. Table 1 shows the summary statistics of the Bitcoin return series. Worth noting is that neither mean nor median appear to be different from 0, when comparing with the standard error, which further supports our assumption that there is no trend in the original series. Further, while the maximum is attained during the bubble in 2014, the minimum stems from the beginning of the series (July 19, 2010), and should, given the low values and the recency of its transition into a an asset that can be used by the public, not receive too much weight. The histogram confirms that the returns approximate a normal distribution.

minimum	median	mean	maximum	standard deviation
-0.450	$1.444 * 10^{-3}$	$6.150 * 10^{-3}$	0.4997	$7.460 * 10^{-2}$

Table 1: Statistics of the Bitcoin returns

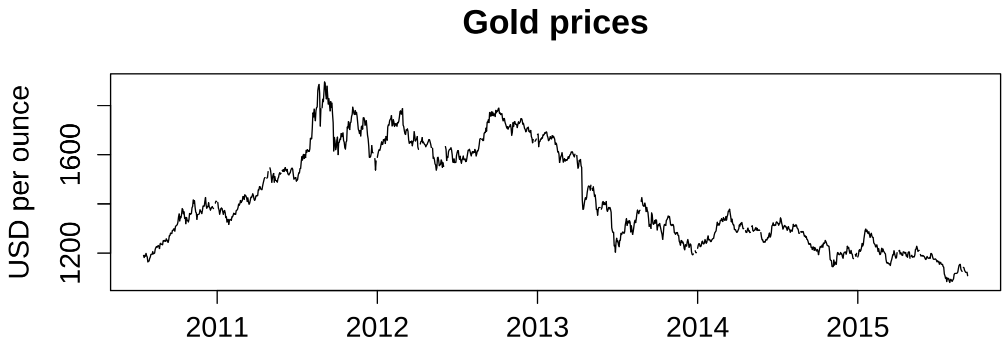

Figure 3: Daily Gold values (for every weekday) of the covered period

2.2 Gold

Figure 3 shows the daily values for gold as observed by the *Deutsche Bundesbank Data Repository*[4]. The daily prices are understood as the result of the morning fixing in London, the unit is $\frac{US\$}{Ounce}$. In 2010, when the data set for the gold series starts, the price is still on the steady increase which seems to show a supposedly exponential growth between 2000 and around 2012 (not covered in figure 3), marking the year where the increase stops and the prices start to decrease in a steady manner, still continuing today. Again, non-stationarity is shown through the change in the mean over time (the Augmented Dickey Fuller test shows a p-value of 0.249, therefore the existence of a unit root cannot be rejected).

To obtain stationarity, we are again transforming the time series into a series showing the percentage changes. For this data set, the absolute changes would be sufficient (since the magnitude of the values that we are fluctuating in-between is rather narrow [between 10^3 and $10^{3.3}$]) to approximate stationarity, but to improve interpretability, and in the context of historical data with significantly lower values (and thus lower absolute volatilities), percentage changes seem to be the better choice. No trend is apparent, trend stationarity can therefore be ruled out.

Figure 4 shows the transformed series. We again define the returns as

[4] `https://www.quandl.com/data/BUNDESBANK/BBK01_WT5511-Gold-Price-USD`; 11.09.2015

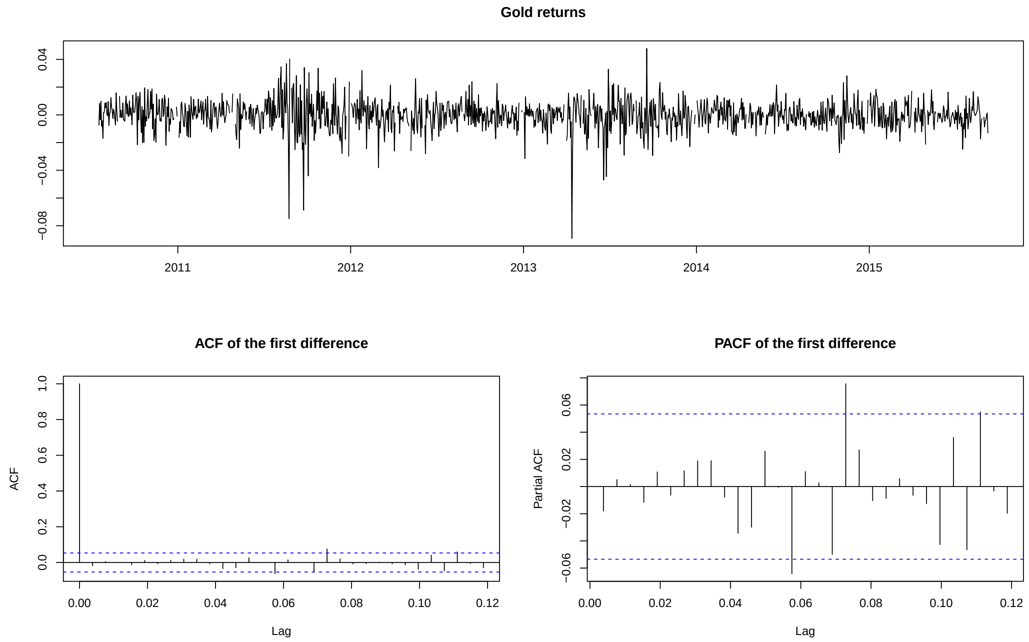

Figure 4: First difference of the logarithms of the gold prices. Below, the ACF and PACF for the first difference of the series

minimum	median	mean	maximum	standard deviation
$-8.913 * 10^{-2}$	0.0	$-4.525 * 10^{-5}$	$5.07 * 10^{-2}$	$1.083 * 10^{-2}$

Table 2: Statistics of the Gold returns

$Goldreturn_t = ln(Gold_t) - ln(Gold_{t-1})$. The ACF and PACF-Functions advocate stationarity. This is confirmed by the ADF-test, which rejects the existence of a unit root on the 99%-level.

Table 2 shows the summary statistics of the *Goldreturn* series. Similar to the *Bitreturn* series, neither mean nor median appear to be different from 0, which supports our assumption that there is no trend in the original series. Note that this only supports that there is no statistically significant trend over our observed period. For the whole period covered by the records of the Gold price, extending over more then the last five years, there might as well be a significant trend. Further, for the covered period, there are some very high changes observed, with the highest and lowest difference being approximately +5% and -9% respectively, both recorded in the year 2013. The histogram confirms approximately normally distributed data, with a few negative outliers.

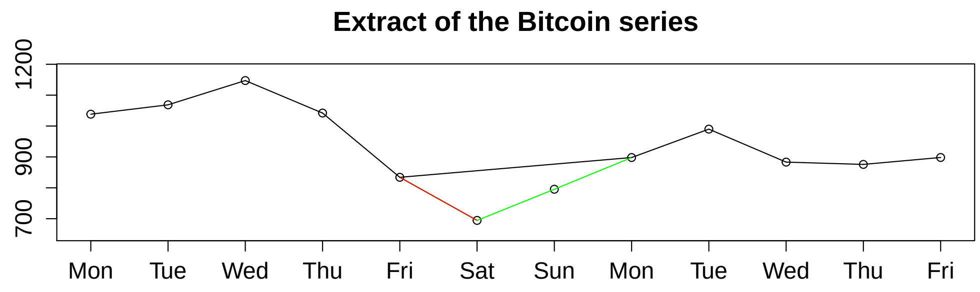

Figure 5: The Bitcoin prices for the period between 02.12.2013 and 13.12.13

2.3 Dummy variables

2.3.1 Bitcoin values for Saturdays and Sundays

Since the Bitcoin is recorded 7 days a week and we are shortening it to 5 days a week to match the gold data, we potentially lose valuable information by removing two data points for every week. In spite of the fact, that the overall weekend movement is captured in the difference between the prices of Friday and Monday, what the shortened series fails to represent are movements in the price that are succeeded by a movement into the opposite direction. Figure 5 shows an example of such a loss of information. The black line shows the movement of the shortened series, while the green and red line show the information about increase and decrease respectively, that gets lost by removing the values for Saturday and Sunday. The Bitcoin is in a way unique in this matter, since it does not rely on an institution to process payments and thus can be traded on public holidays and weekend.

In an attempt to preserve the information from getting lost, we will use a dummy variable defined as follows:

$$Dummy_t(a) = \begin{cases} 1 & \text{if weekend t shows spikes of more than } a\% \\ 0 & \text{otherwise} \end{cases}$$

A spike is defined as an overall movement with at least one positive and one negative return, both showing a magnitude of over $a\%$. The spikes will also be divided into positive (negative) spikes, defined as spikes occurring when the returns of Monday are positive (negative) (figure 5 is an example of a positive spike). Further we will examine 4 different levels of a (1%, 3%, 5% and 10%) for significance, resulting in 12 dummy variables. Table 3 shows their frequencies. A potential effect of these variables will be examined in 2.3.1.

Level	positive spikes	negative spikes	total spikes
1%	56	61	117
3%	21	29	50
5%	11	16	27
10%	2	7	9

Table 3: Frequencies of the different Weekend Dummy Variables

2.3.2 Structural Break

In this section, we define a dummy variable to account for a potential change in the correlation between gold on the Bitcoin. Since its creation, the Bitcoin was subject to a lot of events possibly changing how it is perceived by the public (traders and customers alike). Section 7.1 in the Appendix shows selected events that potentially contributed to a structural change. These events were selected to represent how the Bitcoin is viewed by the media and the public. Excluded are the frequent instances of theft and hacking, since even though they result in a (sometimes significant) change in the Bitcoin returns, they are unlikely to contribute to the change in the gold returns, or a structural change in the relationship between them. Further they are very frequent throughout the whole series due to the nature of the Bitcoin, its susceptibility to sophisticated cyber-attacks.

Throughout the entire history, the Bitcoin's incorporation into the payment process is increased, as shown by the steadily rising number of companies that accept it as a means of payment. The potential break point/period is assumed to be during the Bitcoin's transition into the function of a financial asset (while keeping its function as an easy to use and highly anonymous currency), taking place somewhere in the second half of 2013, where not only a few funds officially start trading the bitcoin, but also Bloomberg enacts a ticker into its systems, therefore establishing it as an easier to monitor asset class. In section 3.3, we will construct a model to determine the date maximizing the possibility of a break point.

3 Models

3.1 Cointegration

Before we use the transformed data that we obtained by removing the stochastic trend through differencing in sections 2.1 and 2.2, we will test the two integrated time series of order 1. Id est, we will test

$$H_0\text{: } \exists\beta \text{ s.t. } Z_t = Y_t + \beta X_t + \epsilon,\ Z_t \sim I(0)$$
$$H_A\text{: no such } \beta \text{ exists.}$$

The test will be conducted using the Engle-Granger cointegration test. Further we will test three time series, using the structural break point (24. October, 2013) that will be shown in 3.3. In all three models, no optimal β can be found such that the series Z_t yields an order of integration of 0. The ADF-test cannot reject the the null hypothesis of an existing unit root in any of the tested models, and thus no evidence for cointegration is found.

3.2 Weekend dummy variables

In this section, we will investigate the 12 dummy variables created in 2.3.1 for statistical significance. Further the effects of spikes in the weekend will be investigated for a total of 5 lags (the next week), namely, the effect of a spike on the returns of Monday to Friday. Hence, we are testing the coefficient β_i with

$$Goldreturn_t = \beta_0 + \beta_i L^k WeekendDummy(i)_t,$$

where L^k is the lag-operator for lag k, $k = \{0, 1, 2, 3, 4\}$, and $WeekendDummy(i)$ is the dummy variable for $a = i$, $i = \{1all, , 1positive, 1negative, ..., 10negative\}$. A spike in the weekend results in the dummy variable showing the value 1 for the corresponding Monday value of t, and 0 otherwise. A table with all the results can be found in the Appendix (table 7 in section 7.2).

There is no statistical evidence for possible correlation between a spike of 3% or more on the weekend and the subsequent changes in the gold returns. Only one lag of a dummy variable (for $a \geq 3$) is significant, but there is no apparent explanation why this specific lag would be significant, therefore it most probably is just fitted noise (since we are dealing with very few observations for $a = 10$).

There are two possible explanations for this. Either an effect does simply not exist, or we cannot provide enough observations in order for the variance to

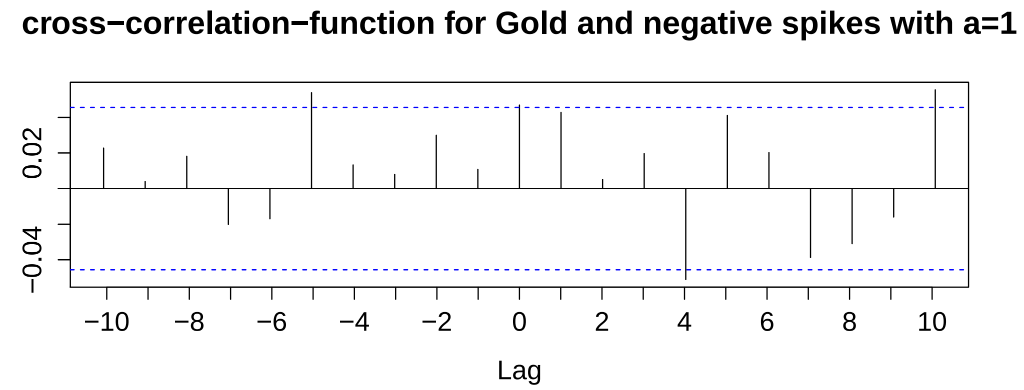

Figure 6: Cross-correlation-function for gold returns and WeekendDummy, the dashed blue line shows the 90% confidence.interval

be low enough to provide sufficient significance levels. We can observe ambiguous effects of an increase in a on the coefficients, therefore an increase in correlation with a higher relative spike seems implausible (if there were to be a relationship between the spikes and the change in the gold price, the most intuitive result would be an increase in the magnitude of the coefficient with an increase in the magnitude of the spike).

As for the 1%-spikes, while there is close to no correlation for spikes occurring while the Bitcoin prize is increasing over the weekend, however during a downwards trend, significant correlation with the returns of gold is observable. Figure 6 shows the cross-correlation-function. While the dummy seems to be correlated with the gold returns, the opposite is less likely (the single significant lag appears to be an outlier and might again be the product of chance, as we are dealing with a 90%-confidence interval and 10 coefficients of the lagged relationship between gold on the Bitcoin-dummy). The average percentage gold price increase over the weekend following a negative spike on the weekend is 0.002407 ($=e^{0.002404} - 1$, as we are working with dummy variables and otherwise logarithmized data. [Halvorsen and Palmquist, 1980:474-475])

What's more, figure 6 shows a supposedly positive trend (however not significant on the 90%-level) for the returns of Monday through Thursday), followed by a reversal in the returns on Friday. In an attempt to find an explanation for this, we have to go back to the definition of the dummy. A *negative spike* corresponds to a spike during a weekend with an overall negative return, and negative returns are by definition more likely to occur in (multiple-period) downward trends. Therefore a negative spike is likely to correspond to a period with high fluctuation during a downwards trend, which, given (one of)

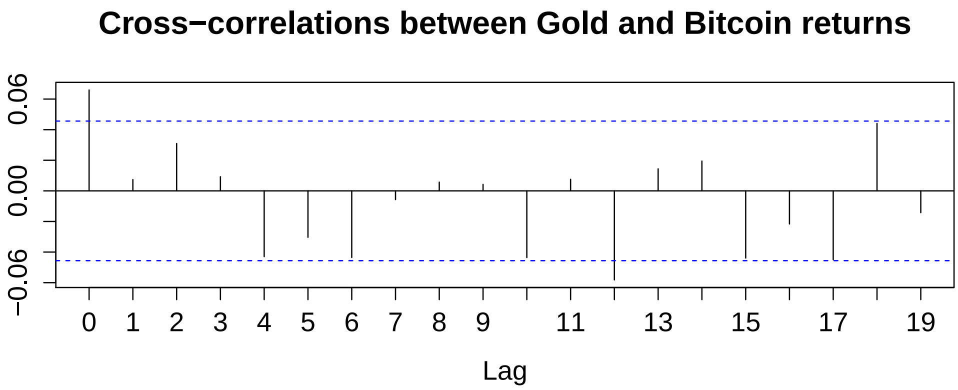

Figure 7: Cross-correlation-function for gold and Bitcoin return series, the dashed blue line shows the 90% confidence.interval

the Bitcoin's supposed function as a speculative asset, is likely to be correlated with uncertainty in the market, supposedly driving gold prices up. The reversal on Friday, on the other hand, shows that this effect has no significant longer-term correlation with the gold price.

3.3 Distributed Lag

In this section, we will make use of a simple regression of the gold return on the Bitcoin return series. Figure 7 shows the cross-correlations for the two series. We can observe that the simultaneously moving return of the Bitcoin is significantly correlated with the gold return. Further, only lag 12 is significant on a 10%-level. However, a lot of the correlations are very close to being statistically significant. Lowering the confidence interval to 85% renders us with 8 significant values (out of 21 estimated coefficients), which corresponds to 38% of the values being significant (while only 15% are implied by the estimation method of the 85%-confidence-interval). With 150% more significant values than the estimation method would allow for in the case of no correlation, it is possible that correlation structures exist.

To find the lags that make up the optimal model we will use forward-selection, iteratively incorporating the next unused lag if the inclusion reduces the information criteria (BIC and AIC), until the addition of no further lag can yield an improvement. Table 4 shows the results. The BIC, incorporating a greater punishment term for additional variables, chooses the random walk as the optimal model, while the AIC chooses an inclusion of the concurrent Bitcoin

Model	BIC	Model	AIC
$Goldreturn_t = \beta_0$	-8041.015	$Goldreturn_t = \beta_0$	-8051.355
no further improvement		$Goldreturn_t = \beta_0 + \beta_1 Bitreturn_t$	-8054.884
		no further improvement	

Table 4: Forward selection using AIC and BIC (error terms omitted in the formulas)

	Best Model
$H_{0,i}$	$Goldreturn_t = \beta_0 + \beta_1 Bitreturn_t + e_t$
$H_{A,i}$	$Goldreturn_t = \beta_0 + \beta_1 Bitreturn_t + \beta_2 DummyStructBreak_{t,i} Bitreturn_t + e_t$

Table 5: Null- and alternative hypothesis for the conducted test

return as a variable. Since, in the model chosen by the AIC, the coefficient β_1 is significant on the 5%-significance-level, we will use the proposition of the AIC. The optimal model according to linear regression is thus

$$Goldreturn_t = -0.00006487 + 0.009543 Bitreturn_t + \epsilon.$$

The standard error of β_1 is 0.004057 and the value for H_0: random walk model is the best model against H_A that adding the Bitcoin return to the model yields a value of $\frac{0.1526179-0.151954}{\frac{0.151954}{1298}} = 5.67107$ which is higher than the 95% significance value for $F_{1,1298}$, 3.8486. The model shows a significant positive relationship between simultaneous movements of the Gold and the Bitcoin price. However the $R^2 = 0.004244$ shows that very little variability in the gold returns is explained by this coefficient.

Structural Breaks

We now will add the dummies for the structural breaks to the linear regression models (the dummies are defined in section 2.3.2). As there is no explanation for a significant intercept in any return-based model regressing gold on Bitcoin, we will only examine the models for a significant change in the coefficients. The hypothesis that we are testing can be found in table 5. $DummyStructBreak_{t,i}$ is the Dummy Variable with value 0 for $t < 1$ and 1 for $t \geq i$, with i tested for all the days between 1. August and 31. December, 2013. Following the approach of Hansen (2001:119-120), we are testing the hypotheses using a Chow-Test for every potential break point. The result can be seen in Figure 8. We can observe significant values between the beginning of October and mid-November, reinforcing our hypothesis of a break point.
The Chow-Statistics show a significant shift in the coefficient, with the highest

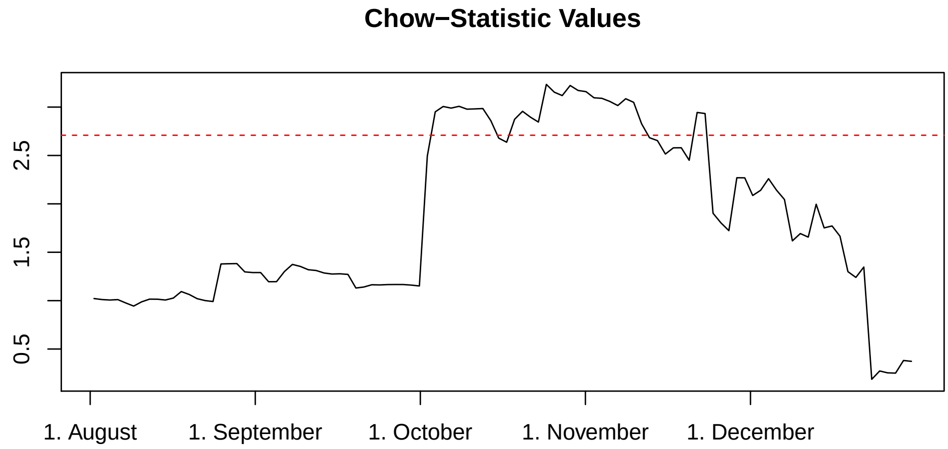

Figure 8: Chow-Statistic values for the observed period between August and December, 2013. The dashed line shows the benchmark for a 90% significance-level

value of 3.23448 being shown on the 24. October, which we will use as our structural break point. Therefore, the chosen model is

$$Goldreturn_t = \beta_0 + \beta_1 Bitreturn_t + \beta_2 DummyStructBreak_{t,24.October} * Bitreturn_t + e_t$$

	Coefficient	Standard Error	Significance level
β_0	0.000137	0.0003	-
β_1	0.01359	0.004597	1%
β_2	-0.017068	0.00949	10%

Both values are statistically significant, but we cannot forget that not β_2 is the coefficient for the time series after the 24. October, but rather $\beta_1 + \beta_2$. While β_1 clearly shows a significant positive relationship before the break, the coefficient for the second part of the series seems to be insignificant since β_1 and β_2 approximately cancel each other out, assuming the variance does not decrease significantly. Regressing gold on Bitcoin for the values after the break point confirms this property, the coefficient is not statistically significant on any level. Figure 9 shows the cross-correlation functions for the two time series before and after the breakpoint.

We can see a major shift in the magnitude of the correlation of the simultaneous returns towards 0 as the Bitcoin supposedly picks up its function as a tradable asset.

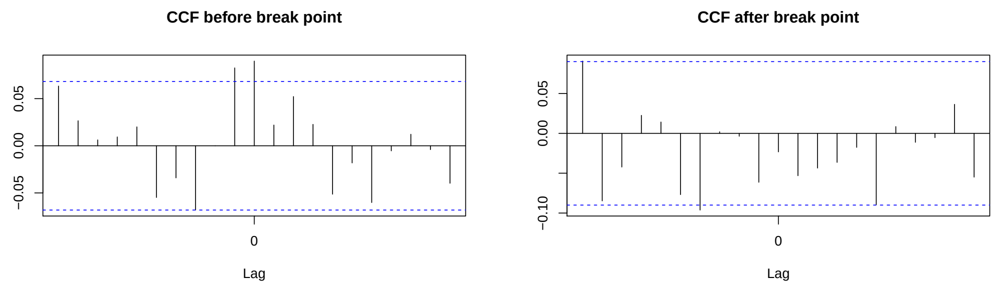

Figure 9: Cross-correlation functions for the gold and Bitcoin series before and after the 24.October, 2013, the break point

3.4 ARIMA transfer model

In this section we will investigate for an optimal ARIMA transfer model, i.e.

$$Goldreturn_t = \beta_0 + \sum_{i=1}^{n_1} \beta_i Goldreturn_{t-i} + \sum_{i=0}^{n_2} \gamma_i Bitreturn_{t-i} + \sum_{i=1}^{n_3} \alpha_i e_{t-i} + e_t$$

The model consists of the common ARIMA structure for the gold returns, but further includes lags of the Bitcoin return series. n1, n2 and n3 are to be estimated and chosen in order to ensure the best fit. As we already know that the series is stationary, the integration will be of order 0.
As predicted by the plot and (partial) autocorrelation-function in figure 4, the gold returns follow an ARIMA(0,0,0) with no intercept. Further only lag 0 of the Bitcoin series is statistically significant on a 5% level. The transfer model with the best fit therefore is the same as the model chosen by the AIC in section 3.3. Also, introducing the dummy variable from section 3.3 does not change the estimated ARIMA(0,0,0) without intercept and therefore yields the same results. Note that incorporating this dummy variable would only change the ARIMA model, if it is a significant omitted variable biasing the AR und MA coefficients of the gold returns, as we are not testing for a change for the breaks in the ARIMA structure itself.

3.5 VAR

In this section we will test several VAR models for optimality. Lag selection will be conducted using AIC and BIC. The results are shown in figure 10. The AIC and BIC chose a lag length of 5 and 1 respectively, while the sometimes preferred AICc ($AIC_c = AIC + \frac{2*k(k+1)}{n-k-1}$) is again minimized by restricting the

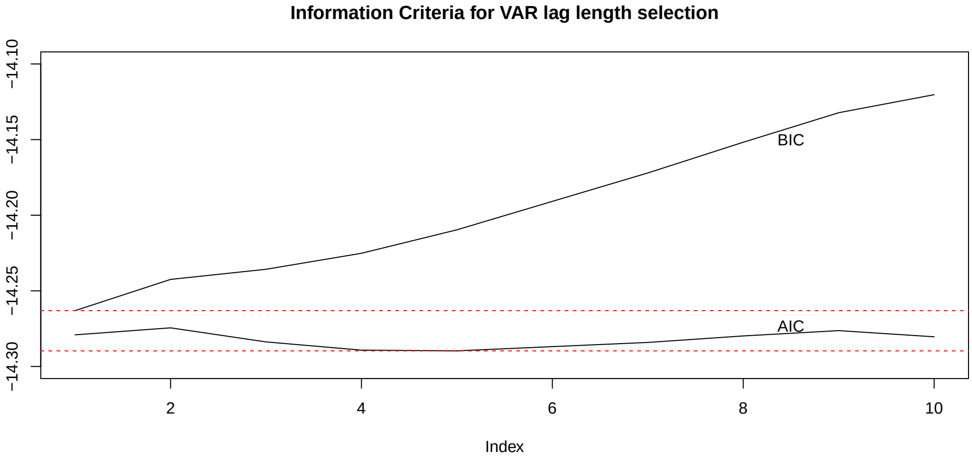

Figure 10: AIC and BIC for the iterative inclusion of Lags 1 to 10 into the VAR model

lag length to 1, which we will therefore use as our preferred model (breaking up the time series at the break point found in 3.3 does not change the optimal lag lengths according to BIC and AIC_c). Therefore, the estimated models is as follows:

$$\begin{pmatrix} Goldreturn_t \\ Bitreturn_t \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \gamma_0 \end{pmatrix} + \begin{pmatrix} \beta_1 & \beta_2 \\ \gamma_1 & \gamma_2 \end{pmatrix} \begin{pmatrix} Goldreturn_{t-1} \\ Bitreturn_{t-1} \end{pmatrix} + \begin{pmatrix} e_t \\ \epsilon_t \end{pmatrix}$$

Details to coefficients and significance values for the long model and the two short models can be found in table 8 in the Appendix. We can observe a clear distinction between the significance of a constant term of the Bitcoin return equation between the first and the second part of the equation. Investigating the movement of the original Bitcoin series shown in figure 1 (before the transformation to stationarity), we can see that in the beginning, the Bitcoin value appreciates over a long period of time, which could explain the constant term, while in the second term, a more stable mean is observable. For our forecasts in section 5, this is not a problem, since we are only going to use the latter part of the series for the predictions of the hold-out sample (where there is no significant constant term). Further we can observe, that the first order autoregressive effect of the Bitcoin vanishes as soon as the Bitcoin gets more credit as a tradable asset, in addition to a qualitative change of the coefficient from a positive to a negative correlation (this might, however, not bare too much meaning, since the second coefficient is highly insignificant and therefore most likely brought up by noise in the data). Further, the relationship between the first lag of gold and the Bitcoin return series changes the sign, a positive correlation in the first part becomes a negative in the second. Overall, this evidence again points towards a structural change within the movements of the Bitcoin series as well as between the two series (namely in the correlation between the gold and the Bitcoin prices).

3.6 VARMA

In this section we will use a VARMA model restricted to AR(1) and MA(1), to examine for a possible effect of moving averages on the simultaneous movement of the gold and Bitcoin returns. We will be using this VARMA model of arbitrarily chosen orders to overcome specification issues (described in brief below) that emerge when transitioning from a univariate to a multivariate ARMA model, exponentially increasing the computation power needed to calculate the best model.

In the univariate case, non-existence of common factors between the coefficients of the moving average and autoregressive lags, in addition to non-stationarity of the models implied by either of the lag-polynomials (i.e., the zeros of the polynomials lie outside the unit circle) are sufficient for the model specification. In the more general, multivariate case, these conditions are not sufficient to obtain a unique model, since for every VARMA model, the coefficient matrices can be premultiplied by any nonsingular matrix of dimension $K \times K$, where K is the number of variables in the model, resulting in a model with the same distribution. Unlike in the univariate case, these new vectors of coefficient matrices do not have to be linearly dependent with the original vector, linear dependency is only the case when the premultiplied matrix is diagonal (for more information on VARMA models and the related specification problems see Lütkepohl 2005: 447-461 and Tsay 1991:248).

As this paper is more concerned with finding a relationship than finding the best fit, it is approximately sufficient to restrict our study to a VARMA be of order (1,1). Therefore, the model is as follows:

$$\begin{pmatrix} Goldreturn_t \\ Bitreturn_t \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \gamma_0 \end{pmatrix} + \begin{pmatrix} \beta_1 & \beta_2 \\ \gamma_1 & \gamma_2 \end{pmatrix} \begin{pmatrix} Goldreturn_{t-1} \\ Bitreturn_{t-1} \end{pmatrix} + \begin{pmatrix} \beta_3 & \beta_4 \\ \gamma_3 & \gamma_4 \end{pmatrix} \begin{pmatrix} e_{t-1} \\ \epsilon_{t-1} \end{pmatrix} + \begin{pmatrix} e_t \\ \epsilon_t \end{pmatrix}$$

Once more, we will be estimating the model for the full series, as well as the data before and after the 24. October, 2013. The results for the estimations can be seen in table 9 in the Appendix. As the eagle-eyed reader correctly noticed, there are no coefficients for the case of the full model. The reason for this is, that a VARMA(1,1) for the entire series cannot be estimated, due to linear dependence of the AR(1) and MA(1) matrices. This stems from the fact that, as the ACF in PACF in tables 2 and 4 suggest (combined with the findings about cross-correlation), the coefficients for the MA(1) and AR(1) for both (individual) series are insignificantly different from 0. Linear dependency of the MA and AR matrices now tell us that further the effect of the errors of one series on the future returns of the other are not significantly different from zero either, leaving us with insignificantly different matrices, that therefore cannot be estimated (for the estimation using the full series).

Both the first and the second part of the series can be computationally estimated, since some coefficients are sufficiently different from zero. However, the coefficients of the estimated AR and MA matrices show big differences in their value, with variances adjusted to their scale. This seems to be the result of difficulty in estimation, since there is no logical explanation why the magnitudes between some of these coefficients would show such a differential. Further their magnitudes are simply too high to be justified, as the models suggest that movements in one series are followed by movements ten times higher in the other series. Therefore the significance values should not be used for the evaluation of the power of these models. An attempt to better evaluate for any modeling and predictive power will take place in the form of the forecast errors in chapter 5.

What we again can compare, is the change in the coefficients between the two models. If there was no change, the AR and MA matrices would be qualitatively similar (i.e., the same transformation that transforms AR from the first to the second period, would transform the MA from the first the the second period). Since this is not the case, further evidence advocating a structural break is given.

4 Bitcoin as compared to other asset classes

As we have seen, there exists evidence for a break point or period around the 24. October, 2013, resulting in two significantly different dependence structures between the gold and the Bitcoin returns. In the first part, a positive correlation between the concurrent and the first lag of the Bitcoin on the gold returns were found, as well as correlation between the first lagged values of the gold and the Bitcoin returns. Comparing this with the potentially qualifying classes shown in section 1.2, we can see that this short term behavior is rather associated with long term investments and returns in the equity markets than the movements of currencies. Further, the series show no cointegration, a property found in time series dependencies between asset classes such as the gold and silver, the early relationship between gold and the Bitcoin is most similar to the relationship between gold and the stock market. This, on the other hand, is counterintuitive, since our break point was marked to be the point where the Bitcoin starts to be perceived as a tradeable asset, through the inclusion of a ticker on Bloomberg, and the establishing of Bitcoin-trading hedge funds that drew media attention.
However, after the break, the coefficients in almost all of the evaluated models become insignificant, thus effectively removing any cross-correlation effect that existed between the two series. This does not approximate any behavior in our compared asset classes. A possible explanation for this is, that as the possibilities to use the bitcoin to acquire goods grows, it depicts a highly novel asset class, used by some for the means of speculation, while being immediately usable as a means of payment, unlike any other financial instrument that is currently in the market. This theory would gain in validity if, after (or during) the break in our relationship, the growing interest in Bitcoin as a speculative asset has also led to an increased interest in it as a means of payment. Only time can tell if the Bitcoin will keep being used in such a variety of ways, or will converge towards a single function, possibly by the so far sole available currency that is not backed by the state. As the Bitcoin shows a behavior that is, as compared to the gold price, different from the other major asset classes, which are commonly used in gold price forecasts, it displays a variable that could potentially increase the power of gold forecasts. In the next chapter, we will thus investigate if the Bitcoin returns show any predictive power for the gold returns. If found, further research has to be conducted if Bitcoin returns can improve forecasting accuracy when included in panel forecasts for the gold returns.

5 Forecasts

In this section, we will investigate the models (and a few extensions of them) that we have seen in chapter 3 for predictive power. Since we are not cross-comparing between different data series, we will evaluate the accuracy by comparing the *Root Mean Squared Errors* (further RMSE) of the forecasts and the corresponding observed values.

$$RMSE_{t,n} = \sqrt{\frac{\sum_{i=t}^{t+n} (Goldreturn_i - \widehat{Goldreturn_i})^2}{n}},$$

where $\widehat{Goldreturn_i}$ is the prediction for the gold returns for period i, denotes the RMSE for the period between t and t+n.
We will be evaluating the predictive power by comparing the forecasts of the last 51 known values in our data set with the observed values. As a benchmark for the forecasts, we will be using the hypothesis that the short term gold prices follow a random walk, which means that our differenced series is best described by $Goldreturn_t = \epsilon_t$ where ϵ_t is the error at time t, and therefore the expected value for t+i at the time t is

$$\widehat{Goldreturn}_{t+i} \equiv E(Goldreturn_{t+i}|t, t-1, ..., 1) = E(\epsilon_{t+i}|t, t-1, ..., 1) = 0, \forall i > 0$$

Note that if this benchmark is not outperformed by the models using Bitcoin returns, the only possible inference is that the Bitcoin series does not add any predictive value, no claims are made that the gold series follows a true random walk.
For any of the further methods to be investigated for predictive values, we will limit the inclusion of lagged values to 1 (prediction on the basis of yesterdays returns and errors, standing for the models preferred by the BIC) and 5 (prediction on the basis of returns and errors during the last work week, the lag length mostly preferred by the AIC). We will not investigate longer lagged models, since there exist plenty of research showing that shorter lagged models outperform their longer counterparts in the short term, which we are interested in (e.g. Hafer and Sheehan, 1989:400 for the case of VAR models).
As we are investigating for added predictive value through inclusion of the Bitcoin series, a second benchmark will be provided through the prediction on the basis of a simple ARMA model on the gold returns, where ARMA(m,n) denotes the model $Goldreturn_t = \beta_0 + \sum_{i=1}^{m} \beta_i Goldreturn_{t-i} + \sum_{j=0}^{n} \gamma_j \epsilon_{t-i}$,

where ϵ_t is the error term at time t and $\gamma_0 = 1$.
For the following models, we will test if they can beat the benchmark:

- ARIMA transfer(5) stands for the model defined in section 3.4, incorporating moving averages and autoregressive lags of order m, as well as m lags of the Bitcoin returns. We are going to use same sized lag lengths for all lagged values, to, as noted above, represent the incorporation of 24 hour and weekly information.

- VAR(m) which stands for a VAR model as defined in section 3.5 with a number m of included autoregressive lags

- VARMA(1,1) which stands for a VARMA model including a autoregressive lag as well as a moving average of order 1.

For the VARMA model, we only include the first order lags, but not the lags up to fifth order. The reason for that is that a VARMA(5,5) requires computational power that exceeds this authors means (a VARMA(5,5) model requires the estimation of 48 coefficients simultaneously). Additionally, longer lagged VARMA models are likely to suffer from multicollinearity (as we have already seen for the VARMA(1,1) model in section 3.6).
As we have strong evidence of a break point occurring in one of the (or between) the series on the 24. October, 2013, we will only be forecasting based on values recorded after this date, as the coefficients for the full series are likely be biased and result in a weaker forecast (or equally strong, if it turns that the Bitcoin series possesses no predictive power for the gold price changes). We will investigate this claim for validity later in this chapter.
As for the models that incorporate the Bitcoin series as an exogenous variable (the two ARIMA transfer), we will only evaluate the horizons where a forecast is possible without forecasting future Bitcoin prices. The reasoning behind this is, that we lack the information to make a good Bitcoin forecast, and incorporating predicted, however in the respective model exogenous regressor variables that behave mostly unpredictable will greatly increase the forecasting variance, while insignificantly improving the forecasting power. This trade-off is unjustifiable, since the risk of fitting noise is increased while only marginally increasing the supplied information. Thus, for the ARIMA transfer models, only a horizon equals to one will be included in the models.

Model	1	3	5
Random Walk	10.62213	10.62213	10.62213
ARMA(1,1)	10.66266	10.6497	10.64185
ARMA(5,5)	10.45289	10.45105	10.36043
ARIMA transfer(1)	10.65101	corresponds to ARMA(1,1)	
ARIMA transfer(5)	10.29776		
VAR(1)	10.60502	10.64483	10.6416
VAR(5)	10.62876	10.57067	10.60615
VARMA(1,1)	10.597	10.646	10.619

Table 6: RMSE*10^2 values for the Forecasts for the Gold returns. Column 2, 3 and 4 denote the horizons 1, 3 and 5 respectively.

The different models are understood as a subsequent addition of more factors to evaluate for an increase in forecasting accuracy.

- Starting point: Random walk
- Adding all the information that the gold series provides: ARMA
- Addition of the *Bitreturn* series: ARIMA transfer
- Allow the *Bitreturn* to be updated endogenously: VAR (This mainly allows us to forecast a horizon bigger than 1, evaluating if estimated Bitcoin returns increase the forecasting power by an amount high enough to let us infer that it is not possible to simply be the result a result of an increase in variance)
- Full model with all the information: VARMA

Table 6 shows the resulting RMSE, with the respective lowest RMSE (for each forecast horizon), and thus the most likely candidate for optimality in the forecast, showing in red. Our main benchmark, the random walk, is beaten by the third benchmark, the ARMA(5,5), on every tested horizon. This result should be viewed with caution, since at the same time, the forecasting accuracy increases when increasing the forecasted horizon (mainly for horizon 5), a counter-intuitive result (since the variance increases when increasing the horizon, due to the usage of estimated values as predictors), which could suggest the low forecast RMSE of the last horizon is a result of chance. Still, the ARMA(5,5) seems to consistently beat the random walk. This is not the case for our second benchmark, the ARMA(1,1), which shows roughly equal RMSE's. As for the models including the *Bitreturn*, the only model that shows

added value to the RMSE figure, is the ARIMA transfer(5) model, incorporating the maximum number of lags for both gold and Bitcoin returns. This positive effect vanishing when transitioning into a VAR model could on one hand mean that moving averages play a significant role in the forecasting of gold returns (which could be an explanation for the improved accuracy using the ARMA model), but could also be a result of the likely linear dependence-problems in the VAR(5) estimation. Finally, the VARMA model does not seem to add significant value to the forecast, as was expected by the estimation problems found in section 3.6.
Finally, the longer lagged models seem to generally (and weakly) outperform their shorter counterparts, the more we increase the forecasting horizon. This makes intuitive since the short models depend on estimated predictors only for horizons past one, while longer lagged models still incorporate a few observed values.
In the following two sections we are going to have a look at how the methods do for forecasting accuracy of the full series and the data up to the break point. The RMSE for the tests can be found in 10 in the Appendix.

Forecasts on the basis of the full series

If we estimate the the future values using all data, as opposed to the estimation using only data after the supposed break point, the forecasts are expected to get worse (under the assumption that predictive value is added in the shorted series), due to a bias in the estimated coefficients. Looking at the RMSE, no model seems to significantly outperform the random walk. However, as this not just the case for models using the Bitcoin price information as an independent variable, but also for our simple ARMA benchmark model, no evidence for a structural break between the two series can be provided on the basis of forecasting performance (however it also cannot be rejected). As for the gold returns, a significant increase in the RMSE when breaking the series in two would provide evidence for a structural change around the in section 3.3 found break point. This drop in accuracy can reflect a change in the coefficients over time in the gold price. To investigate this further, however, is not purpose of this study.

Forecasts on the basis of the first part

Unlike for the data after the structural break, data recorded before the 24. October, 2013, does not seem to yield any kind of predictive power (neither auto-regressive, nor in the relationship between the two series) for the future gold returns. Combining this with the inferences made in the section on the full series forecast, the conclusion seems likely that rather than a change in the relationship of the auto-regressive and moving average terms in the *Goldreturn* ARMA model, a significant effect has only been introduced in the latter part of the series, and has not been prevalent yet in the beginning.

6 Conclusion

In our study, we have focused on the contributions that the Bitcoin makes in the modeling and forecasting of gold returns. The results were used to aid in the determination of the function of the Bitcoin.

In the introduction, an overview on the research about the Bitcoin was given and the potential functionalities were listed. This was followed up by a survey showing the relevant interdependencies between the compared asset classes and gold. In the next chapter, an overview over the used data was given, and the data was transformed to stationarity. We have found, that gold, as well as Bitcoin prices, are integrated of order 1, and we thus created series for the returns. In the third chapter, we developed a series of models to test for the correlation between gold and Bitcoin returns. The main finding was, that a structural change took place, when the Bitcoin started to be regarded as a tradable asset. Most of the models show significant differences between the coefficients for the first and the second part of the series, divided by the break point of the 24. October, 2013. In the fourth chapter, we used the insights that we gained in the previous chapter to compare the movements of the Bitcoin, as compared to the gold returns, with the potential functional classes that we pointed out in the introduction. It was found, that the structures after the found break point do not correspond to any of the relevant asset classes. We concluded, that due to the different movement of the Bitcoin, as compared to the other asset classes, it might be useful in gold forecasts, as long as it yields a predictive value. Thus, in chapter 5 we tested all the relevant models for predictive power, using a hold-out sample, and comparing to a random walk and two ARMA benchmarks. We found, that a model that incorporates 5 exogenous lags of the Bitcoin returns is able to beat the benchmark on the respective hold-out sample on the first horizon.

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7 Appendix

7.1 Major events in the history of the Bitcoin

July 2010	**Mt Gox becomes platform for Bitcoin exchange**
	`https://en.wikipedia.org/wiki/Mt._Gox#Founding`; 14.10.2015
January 2011	**Foundation of Silk Road, platform using Bitcoin as payment for the distribution of drugs**
	`https://en.wikipedia.org/wiki/Silk_Road_(marketplace)`;14.10.2015
February 2011	**Bitcoin price surpasses 1 USD, media attention increases**
March 2011	**Several countries open up Bitcoin exchanges**
April 2011	**Time Magazine publishes article "Online Cash Bitcoin Could Challenge Governments, Banks"**
	`http://techland.time.com/2011/04/16/online-cash-bitcoin-could-challenge-governments/`;14.10.2015
June 2011	**Wikileaks accepts Bitcoins as a means of payment**
	`http://www.deathandtaxesmag.com/104244/wikileaks-now-accepting-bitcoin-donations/`;14.10.2015
June 2012	**Coinbase opens up, offering a Bitcoin wallet service**
	`http://allthingsd.com/20120629/betting-on-bitcoin-coinbase-wants-to-be-the-paypal-of-the-internet-only-currency/`;14.10.2015
September 2012	**London 2012 Bitcoin Conference**
	`https://bitcoinmagazine.com/articles/the-london-2012-bitcoin-conference-1343146418`;14.10.2015
November 2012	**Wordpress accepts Bitcoins as a mean of payment**
	`https://bitcoinmagazine.com/articles/wordpress-accepts-bitcoin-1353043485`;14.10.2015
December 2012	**Foundation of Bitcoin Central (licensed bank)**
	`http://www.engadget.com/2012/12/09/bitcoin-exchange-bitcoin-central-licensed-bank/`;14.10.2015
February 2013	**Foundation of PizzaForCoins.com**
	`http://www.huffingtonpost.com/2013/02/12/pizzaforcoins-bitcoins_n_2671838.html`;14.10.2015
	Mega starts accepting Bitcoins as a mean of payment
	`http://www.wired.co.uk/news/archive/2013-02/19/mega-bitcoin`;14.10.2015
March 2013	**FinCen defines stance on bitcoin**
	`http://fincen.gov/statutes_regs/guidance/html/FIN-2013-G001.html`;14.10.2015
	PrimeDice.com launches (online casino accepting Bitcoins)
	`http://www.coindesk.com/what-will-gambling-do-to-the-bitcoin-block-chain/`;14.10.2015
July 2013	**Winklevoss Bitcoin Trust filed**
	`http://www.coindesk.com/winklevoss-twins-file-for-20m-ipo-of-bitcoin-trust-fund/`;14.10.2015
August 2013	**Adding of Bitcoin ticker to Bloomberg**
	`http://techcrunch.com/2013/08/09/bitcoin-ticker-available-on-bloomberg-terminal/`;14.10.2015
September 2013	**Launch of *Bitcoin Investment Trust***
	`http://www.coindesk.com/secondmarket-launches-bitcoin-investment-trust-invests-2-million/`;14.10.2015
Nov 2013	**Baidu, Subway, Shopify accept Bitcoin as a means of payment**
December 2013	**China Central Bank bans Bitcoin transactions**
	`http://www.bloomberg.com/news/articles/2013-12-05/china-s-pboc-bans-financial-companies-from-bitcoin-transactions`;14.10.2015
	Pantera Capital launches Bitcoin fund
	`http://www.businessinsider.com/fortress-launches-bitcoin-fund-2013-12?IR=T`;14.10.2015

7.2 Tables

dummy variable	lag	coefficient estimate	standard error	significance level
All Spikes, 1%	0	0.00200	0.00105	10%
	1	0.001370	0.00126	-
	2	0.000260	0.00154	-
	3	-0.00052	0.00120	-
	4	-0.00152	0.00105	-
Positive Spikes, 1%	0	0.00136	0.00148	-
	1	-0.00010	0.00181	-
	2	0.000590	0.00228	-
	3	-0.00213	0.00169	-
	4	-0.00016	0.00149	-
Negative Spikes, 1%	0	0.0024	0.00142	10%
	1	0.00253	0.00168	-
	2	-0.000011	0.00201	-
	3	0.00104	0.00164	-
	4	-0.00263	0.00142	10%
All Spikes, 3%	0	0.00127	0.00156	-
	1	0.00190	0.00188	-
	2	0.00341	0.00250	-
	3	0.00033	0.00175	-
	4	-0.0007	0.00157	-
Positive Spikes, 3%	0	0.00291	0.00204	-
	1	0.00354	0.00241	-
	2	0.00273	0.00313	-
	3	0.00237	0.00236	-
	4	-0.0018	0.00204	-
Negative Spikes, 3%	0	-0.00104	0.00239	-
	1	-0.00063	0.00294	-
	2	0.004450	0.00408	-
	3	-0.00221	0.00262	-
	4	0.00084	0.00239	-
All Spikes, 5%	0	0.00088	0.00211	-
	1	0.0001	0.00241	-
	2	0.00336	0.00326	-
	3	0.00205	0.00242	-
	4	-0.00126	0.00211	-
Positive Spikes, 5%	0	-0.00255	0.00328	-
	1	-0.00474	0.00387	-
	2	0.00716	0.00538	-
	3	-0.00165	0.00359	-
	4	0.00011	0.00329	-
Negative Spikes, 5%	0	0.00323	0.00273	-
	1	0.00309	0.00305	-
	2	0.00114	0.00408	-
	3	0.00504	0.00325	-
	4	-0.00218	0.00273	-
All Spikes, 10%	0	0.00267	0.00363	-
	1	0.01026	0.00413	-
	2	0.00557	0.00538	-
	3	0.00530	0.00406	-
	4	-0.00201	0.00364	-
Positive Spikes, 10%	0	0.00297	0.00767	-
	1	0.00897	0.00772	-
	2	0.0078	0.01074	-
	3	-0.00501	0.00758	-
	4	-0.0061	0.00769	-
Negative Spikes, 10%	0	0.00258	0.00411	-
	1	0.01073	0.00488	-
	2	0.00481	0.00621	-
	3	0.00941	0.0048	5%
	4	-0.00083	0.00412	-

Table 7: All examined weekend dummy variables for all lags, with corresponding coefficients and significance values

coefficient	estimate	standard deviation	significance level
Full data set			
β_0	-0.000007	0.000304	-
β_1	-0.013095	0.028065	-
β_2	0.0009564	0.004077	-
γ_0	0.005906	0.002072	1 %
γ_1	0.331342	0.191020	10 %
γ_2	0.052107	0.027750	10 %
Data set up to the 24. October, 2013			
β_0	0.000119	0.000425	-
β_1	-0.03634	0.034983	-
β_2	0.003752	0.005189	-
γ_0	0.008495	0.002846	1%
γ_1	0.499824	0.234277	5 %
γ_2	0.094648	0.034753	1 %
Data set after the 24. October, 2013			
β_0	-0.000242	0.0003892	-
β_1	0.0665632	0.0478438	-
β_2	-0.007309	0.0065127	-
γ_0	0.0004997	0.0027335	-
γ_1	-0.488895	0.3360630	-
γ_2	-0.111599	0.0457463	5 %

Table 8: Coefficients, variances and significance values for the VAR(1)-models of the three series

coefficient	estimate	standard deviation	significance level
Data set up to the 24. October, 2013			
β_0	0.000055609	0.00019281	-
β_1	0.428753438	1.92473936	-
β_2	0.002503918	0.02655511	-
β_3	-0.46707800	1.80962584	-
β_4	0.002211264	0.05071374	-
γ_0	0.006297171	0.03446265	-
γ_1	9.977559527	11.1071156	-
γ_2	0.198125511	3.36766205	-
γ_3	-9.50053010	10.9054247	-
γ_4	-0.08473680	3.48727915	-
Data set up after the 24. October, 2013			
β_0	-0.0000300	0.00009003909	-
β_1	0.85970320	0.3525320	5%
β_2	0.00271743	0.02077609	-
β_3	-0.8464308	0.3510572	5%
β_4	-0.0101980	0.01625383	-
γ_0	-0.0018624	0.004684362	-
γ_1	-11.361388	5.800762056	10%
γ_2	0.19842240	0.416576850	-
γ_3	11.1848667	5.796571992	10%
γ_4	-0.3350433	0.410095046	-

Table 9: Coefficients, variances and significance values for the VARMA(1,1)-models of the two series

Model	1	3	5
Random Walk[1]	10.6221	10.6221	10.6221
ARMA(1,1)[1]	10.6353	10.6276	10.6267
ARMA(5,5)[1]	10.7390	10.7303	10.6153
ARIMA transfer(1)[1]	10.6408	corresponds to ARMA(1,1)	
ARIMA transfer(5)[1]	10.7918		
VAR(1)[1]	10.6401	10.6276	10.6267
VAR(5)[1]	10.6375	10.6063	10.6227
VARMA(1,1)[1]	Model cannot be estimated		
Random Walk[2]	13.8244	13.8244	13.8244
ARMA(1,1)[2]	13.907	13.8343	13.8292
ARMA(5,5)[2]	14.0350	14.1142	14.1919
ARIMA transfer(1)[2]	13.9010	corresponds to ARMA(1,1)	
ARIMA transfer(5)[2]	14.4345		
VAR(1)[2]	13.8765	13.8295	13.8285
VAR(5)[2]	13.8388	13.8053	13.8281
VARMA(1,1)[2]	13.9064	13.8229	13.8319

Table 10: Gold return forecast RMSE*10^2 values for the all used models, [1] denotes forecasting for the full data series, [2] denotes forecasting for the first part of the series, up to the break point. Column 2, 3 and 4 denote the horizons 1, 3 and 5 respectively.