How price charts affect stock price forecasts

*By Christian Tassler**

Abstract. This experimental paper exhibits how price paths affect forecasting behaviour. In a setting of various charts subjects make predictions. I find that trend continuation and mean reversion are among the major emerging pattern and that the use of price paths that differ in their time frame can lead to significantly different forecasts. Furthermore, I infer that most of those intuition afflicted decisions that result in pattern can mostly be linked to the anchor and representativeness heuristic, in which subjects take past price movements as indicative for future ones. This paper thus gathers the pattern that surface when individuals are tasked with stock price forecasting and explores the differences in forecasting pattern that arise from different price paths.

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Outline

1. Introduction

A stock price, representing the cost of a company's single share, is influenced by three major forces. Those are; fundamental factors, technical factors and market sentiment. The size of the part of a company's profit which goes to each holder of a share, i.e. the earnings per share, is a fundamental factor that impacts its price. This fundamental value can be considered the stock's intrinsic value, which excludes the market value and solely depends on the security's earning potential (Fama 1965). Technical factors such as the current inflation rate and the liquidity of the company influence the price of a stock as well. Lastly, market sentiment, i.e. the general attitude of investors, plays an ample role as well as stock prices are partly driven by the investors' expectations (Aronson 2011).

Under the efficient-market hypothesis (EMH), stock prices are supposed to mirror all available information, which implies that stock prices exclusively react to new information, making it impossible to beat the market (Basu 1977). In other words, stock prices trade at their fair value and thus profits can only be made by coincidence. However, stock prices are also partly determined by the investors' fears and expectations. Their predictions can thus drive share prices away from their intrinsic value. Therefore, the EMH is rejected by a number of researchers (Aronson 2011) and investors (Buffett 1984). In addition, the recent financial crisis of 2008 has lead to a renewed criticism in which authors hold the EMH responsible for underestimating dangers in asset bubbles (Nocera 2009). In the pursuit of predicting future stock prices and yielding profits, two conventional methods exist.

The fundamental analysis, a widely used technique, scrutinizes a company's financial health as well as its competition. Hereby, the company's past performance, the quality of its management and its economic outlooks are evaluated (Abarbanell *et al.*1997). One attempts to measure the intrinsic value of the share with the goal of making forecasts. Fundamental analysts hold the view that in the long-run, prices converge to their intrinsic value and therefore profits can be earned, for instance, by buying wrongly under priced shares, anticipating a correction in value.

In contrast to the fundamental analysis, technical analysts hold the view that all information is reflected in a security's price and are more interested in the pattern of a company's stock price path. In order to use the pattern in stock price time series, technical analysis uses statistical tools and indicators to identify specific pattern that they consider to recur, in other words they assume that those chart pattern repeat itself to a statistically exploitable extent.

Despite the technical and the fundamental analysis being in contrast to each other, both are often considered to be complementary (Bettman et al. 2009). However, both are rejected by the EMH which argues that prices evolve stochastically.

Although the literature has come up with a (rather normative) theory in which markets are efficient, still no genuine consent about the way stock prices are supposed to evolve and to be investigated best, exists among academics and professionals. Therefore, the second part of this paper introduces the two fields of stock price dynamics and demonstrates, through the emergence and recurrence of pattern, the invalidity of the EMH. Those pattern that emerge through intuition and biases lead to the idea of attempting to discover the pattern that emerge from specific paths. Part three explains the experimental design, the data and gives several examples of used price paths. Subsequently, part four of this paper gathers and analyzes the results. The last and fifth part consists of an overall summary of the study, including some implications, extensions as well as limitations, eventually finishing with a conclusion.

2. Stock price behaviour and stock price forecasting

There exist two groups that perceive stock price dynamics contrastingly, chartists and proponents of the random walk theory.

A chartist makes use of technical analysis and investigates stock price paths in an attempt to extract pattern that may allow him to make accurate price predictions. The underlying assumption is that past stock prices reflect all the information about a company needed to predict future stock prices, whose movements are thus not random (Frankel and Froot 1990). Many pattern are considered to recur or to give indications of future movements. In addition to using statistical tools, chartists might add fundamental analysis to complement the technical analysis and strengthen their predictions.

In contrast, the adherents of the random walk theory argue that stock prices follow a stochastic process. They assume price changes to be independent, i.e. price changes in t are independent of price changes in t_{-1}. It is confessed however, that perfect independence is difficult to reach (Fama 1965) and as long as dependence of successive price variations does not exceed some minimum level, according to Fama (1995), the independence assumption is considered valid and the random walk theory *can* be an accurate representation of reality.

From a general point of view, the existence of recurring stock price pattern reflect mechanisms that are detached from rationality. Stock prices dynamics can thus be regarded as an agglomeration of psychological factors and expectations. As mentioned earlier, investors' expectations contribute to stock price dynamics and as agents are primarily motivated by whim (Fama1965), making use of their intuition, biases lead investors to making mistakes (Burton 2003). Also, the average investor may not statistically investigate stock price charts intensively nor possesses the necessary fundamental information to make rationally optimal predictions. Individual investors in the stock market might not act as rational as the EMH assumes.

For instance, it is found that most investors tend to invest more in risky assets in spring while they prefer safer assets in autumn (Kamstra 2015) and that overall stock prices tend to drop on Monday mornings (Harris 1986). Regarding seasonal and temporal pattern, it becomes evident that stock prices are able to deviate from the "random walk", hence not following a stochastic process. In addition, contrasting with Fama(1995), Lo *et al.* (1988) found that stock prices cannot be considered to follow a random walk and in an experimental study and Glaser *et al.*(2007a) found that overconfidence was correlated among all experimental subjects, pointing to judgmental characteristics in forecasting behaviour. Furthermore, framing effects seem to play a role in forecasting stock prices as well. When asking for stock prices, findings point to mean reversion and when participants forecast a stock return, Glaser *et al.*(2007b) found that subjects were following trends.

The normative random walk theory is based on the efficient market hypothesis, assuming complete rationality. If all market participants would act in an exclusively rational manner and the market was genuinely efficient, then price movements would evolve according to a stochastic process. However, the random walk theory and EMH are rejected because the market becomes inefficient due to stock prices being driven to a part by psychological factors. Pattern emerge due to suboptimal investment behaviour and phenomena occur which show that it is quite wrong to assume the average investor reflecting homo economicus. Being limited by statistical skills and characterised by not always conducting rigorous analysis of a companies' intrinsic values, individual decisions to anticipate future stock prices are marked by psychological factors and this accumulation gives way for pattern to emerge, return and persist.

The EMH as well as the random walk theory have been rejected by many (Lo *et al* 1988, Quiggin 2013, Man Lui and Chong 2013) and it can be assumed that the market does not work in an efficient way so that past stock prices influence future ones (Arson 2011). Hence technical analysis becomes a legitimate tool. In fact, many individuals and investors might intuitively anticipate stock prices by exclusively possessing basic information and by investigating stock price charts, for instance attempting to simply follow an upward trend (Covel 2004) and sell the security after its price increased.

Having stated that the collective judgement mistakes of investors lead to the emergence of pattern, it is interesting to investigate the price path pattern that induce individuals to make specific predictions and to what extent price charts affect stock price forecasts in general. This paper aims therefore to conduct an explorative experiment in which subjects make predictions using price charts.

3. Experimental Design

The fact that stock price dynamics are partly influenced by psychological factors (i.e. biases , intuition, whim, heuristics etc.) instead of exclusively high rationality has led to the idea of conducting a stock price forecasting experiment in which subjects predict stock prices using price charts in order to learn more about chart-based forecasting behaviour. In this setting, stock price forecasting is making an educated guess by using stock price charts while possessing some basic information about the company in question.

3.1 Data and Methodology

In this research paper, the subjects are confronted with several price charts. The charts in this study contain particular pattern and concern stock prices of large multinational companies, so as to meet the assumption of possessing basic knowledge about the company one is investing in. Thus it will be investigated how specific pattern and how same charts with different time frames affect forecasting behaviour. Therefore, the subjects deal with two different kinds of time frames, where by one consists of a three month time frame and the second kind of charts covers a twelve month period. I split up the subjects in two groups, each member of a group has to give a price prediction for one month in the future. The study hence consists of a forecasting exercise in which the displayed stock price paths reflect specific pattern, in order to see what forecasting pattern emerge.

The data is collected from a sample of in total 94 respondents. 45 respondents for the 3 month period charts and 49 subjects answered the 12 month period survey. Most of the subjects are under graduate students and have some background in economics, however no particular background in finance. As Glaser *et al.* (2007b) exposed in their research, there is no significant difference between professional, individual or student investors and even professional investors are subject to biases of underestimation (Deaves *et al.* 2010). Furthermore, practice in stock market can even be detrimental to a certain extent resulting in overconfidence (Glaser *et al.* 2007b). Hence I consider students as respondents to be suitable participants. The data of the several stock prices stems from the 19th April and predictions are supposed to be made for a month in the future, hence the estimations have been made in mid April for mid May.

3.2 Stock price paths

The following types of stock price paths are displayed multiple times and in order to make further reading more comfortable, all the charts are displayed at the end of this section. There exist counter examples as well, so we might strengthen our findings by checking for contrasting findings in contrasting price paths. In other words, when I present subjects charts with strong trends, then I will also display charts with weak trends or nonexistent trends.

3.2.1. Trends in charts

As has been briefly mentioned in section 1, investors can earn profits by following trends (Covel 2004). In fact, lots of market participants act in this manner whether it is the stock-, bond- or currency market.

Charts that display trends (Fig. 1) will show to what extent the prediction is influenced by a trend and how this relation evolves by using different levels of trend intensity. Hence several trends with different intensities are employed ranging from weak to strong. Finding trend following predictions would confirm the tendency of individuals to anticipate further increases based on earlier ones and hence considering earlier movements representative for future ones, which would demonstrate the impact of charts in stock price forecasting. For up/downward sloping time series, Glaser *et al.* (2007) find that a trade-off between trend following and mean reversion can result from framing effects. Hopefully, this study allows to explore when subjects decide to follow trends or make a prediction that rather equals the displayed mean. In order to explore this, charts have been used that display several kinds of trends.

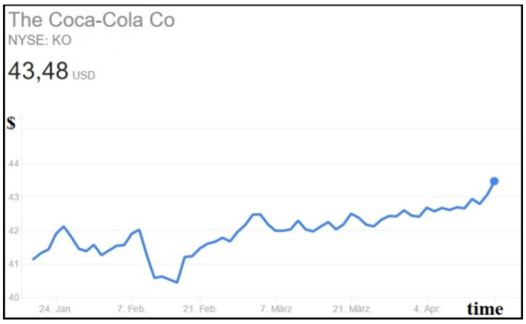


Figure 1 Vertical axis : USD Horizontal axis : time
Coca Cola's 3 month chart displays weak upward trend

3.2.2. Volatility in charts

By using charts that display different levels of volatility, i.e. more or less fluctuations, we can analyze how volatility influences stock price forecasting. As stock price predictions are by a certain extent driven by the investors' expectations (Fama 1965), it is important to know what expectations result from time series that include several levels of volatility. It was found that professional stock market analysts frequently underestimate volatilities of stock returns (Deaves *et al.*2010) and considerable volatility equals higher uncertainty regarding in which direction the price is more likely to move in the near future. Therefore the current paper uses charts that display various levels of volatility as well as charts with different volatilities that are also intertwined in trends so as to see how those characteristics affect predictions. As subjects in past studies make use of past price volatility for future volatility (Grosshans and Zeisberger 2016), it will be interesting to see the resulting pattern.

For instance, while the stock price of Samsung Electronics (Figure 2) seems to follow an upward trend with a rather low dispersion of the price around the trend, Nestlé's stock (Figure 3) prices fluctuate way more and no obvious trend can be detected.

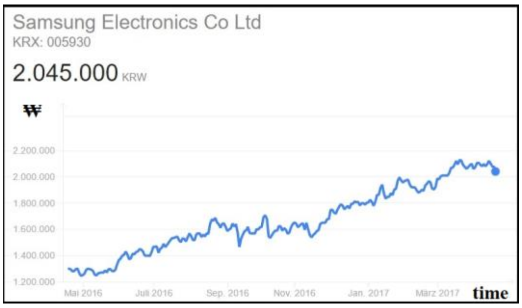


Figure 2 Samsung 12 month chart : clear upward trend with decent volatility
Vertical axis : KRW Horizontal axis : time

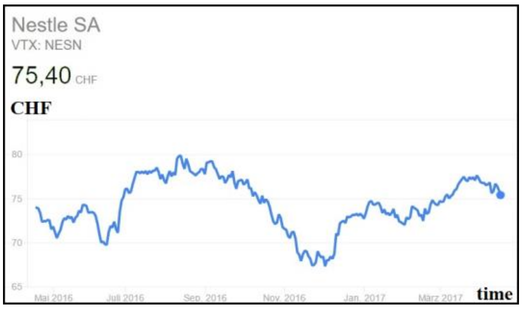


Figure 3 Nestle 12 month chart: no particular trend with high volatility
Vertical axis : CHF Horizontal axis : time

3.2.3. Charts displaying different time frames

According to Glaser *et al.*(2007b) there is no general consent about how long investors look back in time before they make a prediction. This is actually quite crucial as price paths can differ when different time frames are employed. Therefore, the stock price charts the subjects will be confronted with, exist in two different time frames.

Stock price increases in the long term can be interweaved in a short or medium term decrease. Those short-term and long-term pattern affect the perception of what direction the stock price is more likely to move, differently. While the three month period time frame can display high price fluctuations, the twelve month period might not capture the volatility to a same extent due to increase of the scale.

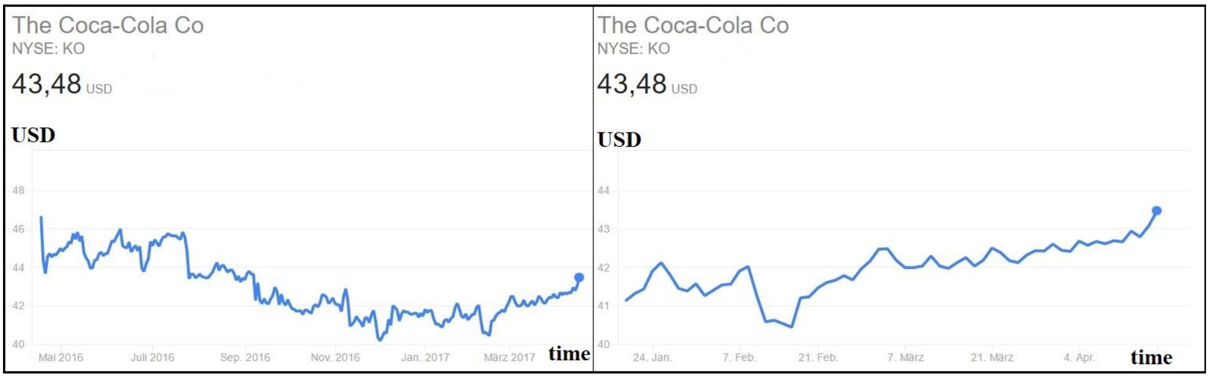


Figure 4 12 month (lhs.) and 3 month (rhs.) period in comparison
Vertical axis : USD Horizontal axis : time

It is therefore useful to examine charts that resemble each other to a larger extent (i.e. the 3 month period chart looks similar to the 12 month period chart), as can be seen on Figure 4, but also to compare forecasts stemming from charts that, at first sight, display strongly different characteristics in terms of trend and volatility (Figure 5).

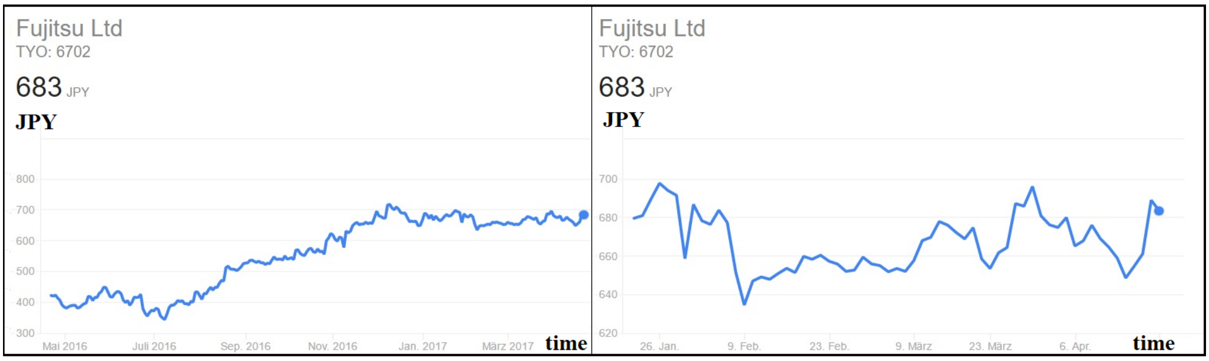


Figure 5 12 month (lhs.) and 3 month (rhs.) period in comparison
Vertical axis : JPY Horizontal axis : time

<u>Please note: the following abbreviations will be used:</u>

<u>Company Names</u>

Coca Cola Company = Coca Cola , Royal Dutch Shell Company = Shell
Nike Inc = Nike ,Samsung Electronics Company Limited = Samsung ,
Gillette India Limited = Gillette , Nestlé SA = Nestlé, Toshiba Corp = Toshiba ,
Fujitsu Limited = Fujitsu , Telefonaktiebolaget Ericsson = Ericsson , Bayer AG = Bayer , Deutsche Bank AG = Deutsche Bank , Alphabet Inc = Google.

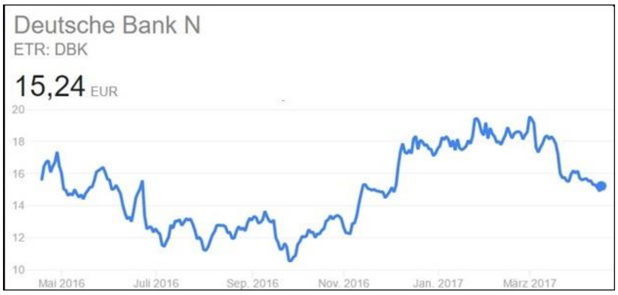
<u>Currencies</u>

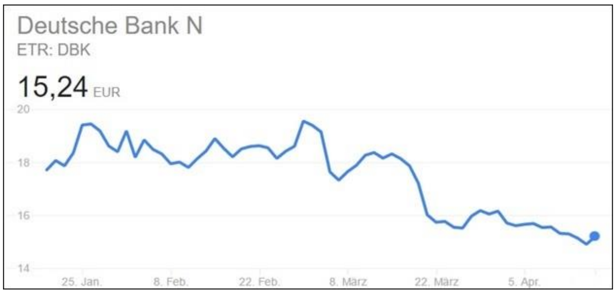
EUR = EURO, SEK = Swedish Crown, INR = Indian Rupee (₹),
JPY = Japanese Yen (¥), USD = United States Dollar,
CHF = Swiss Franc , KRW = Korean Won (₩)

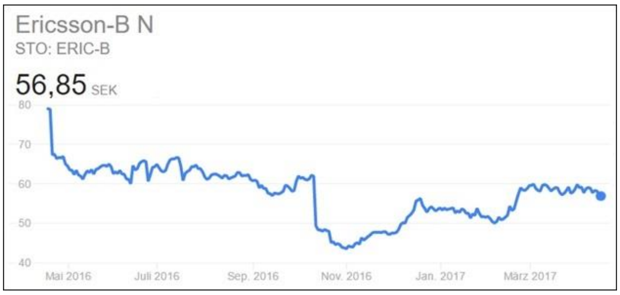
3.3. All experimental charts

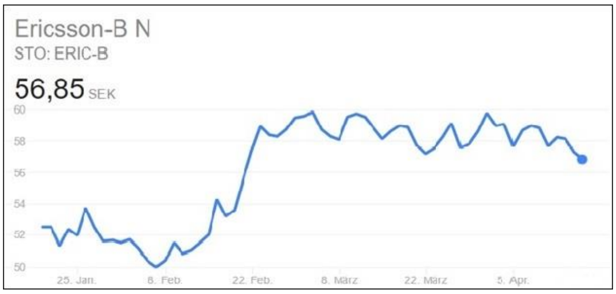
On the left hand side : 12 month period

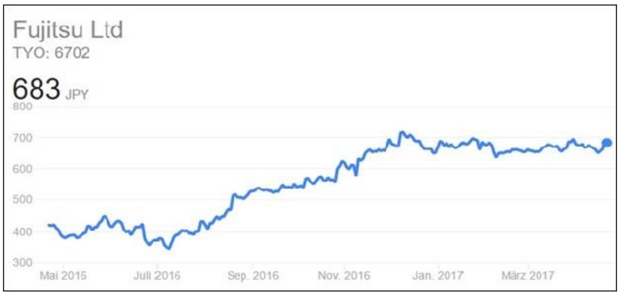
On the right hand side : 3 month period

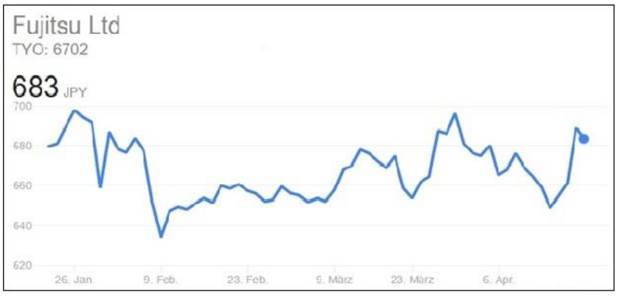


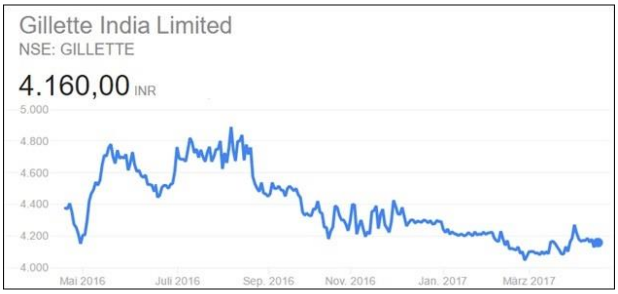


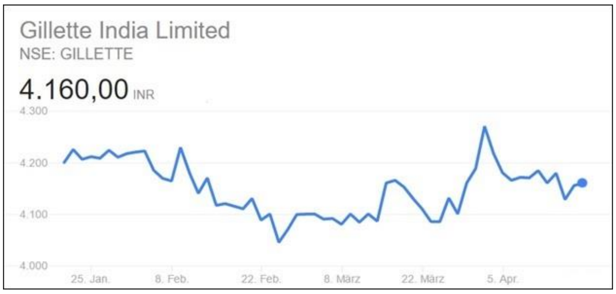


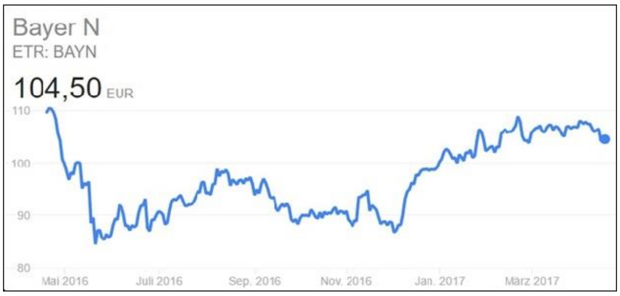








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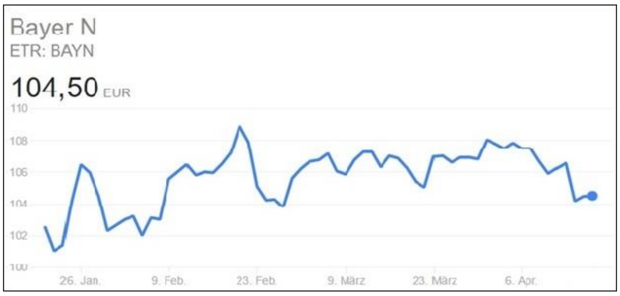
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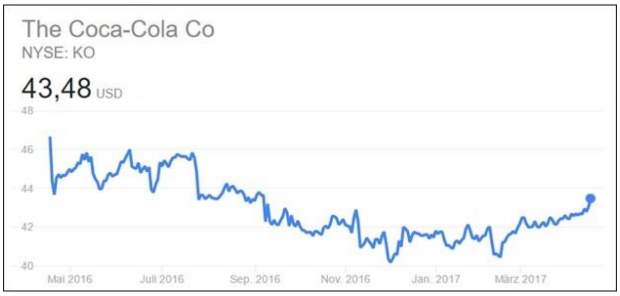
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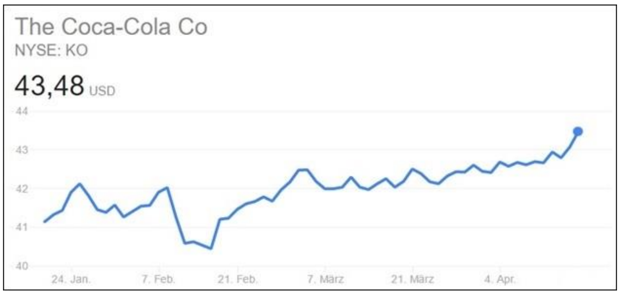
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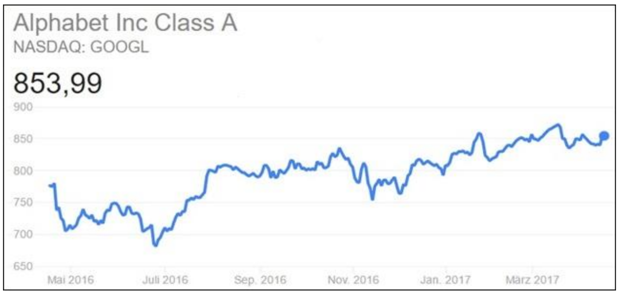
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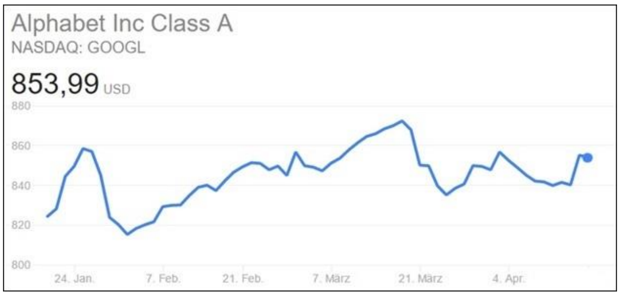
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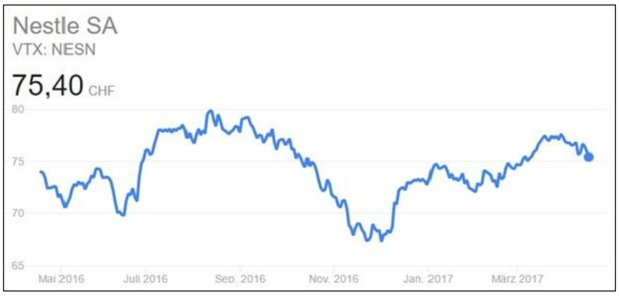
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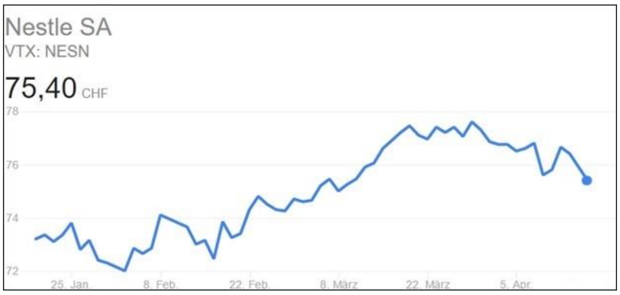
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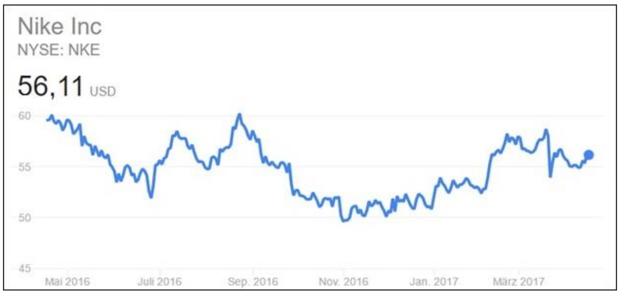
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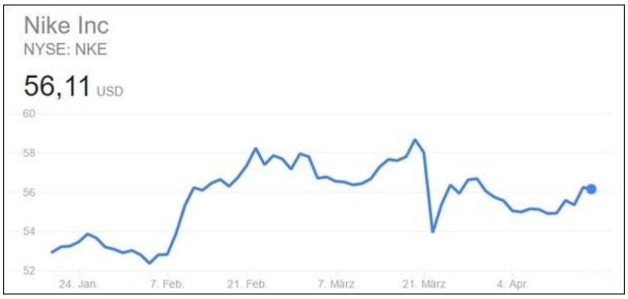
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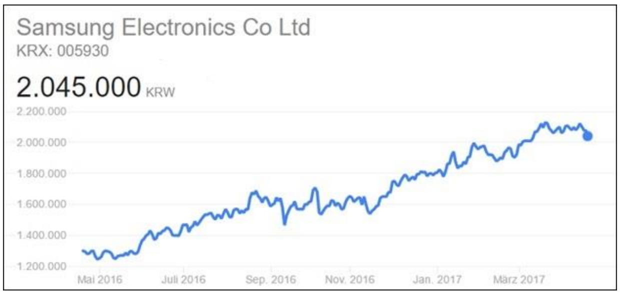
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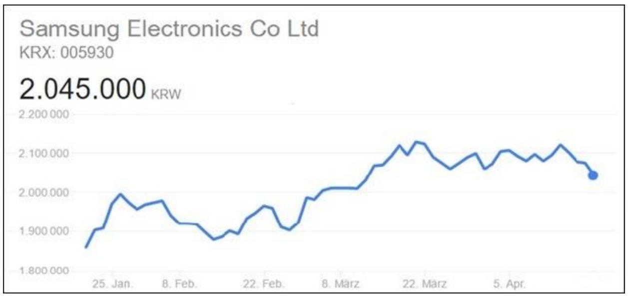
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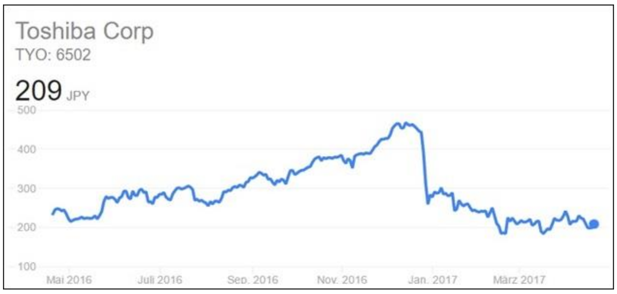
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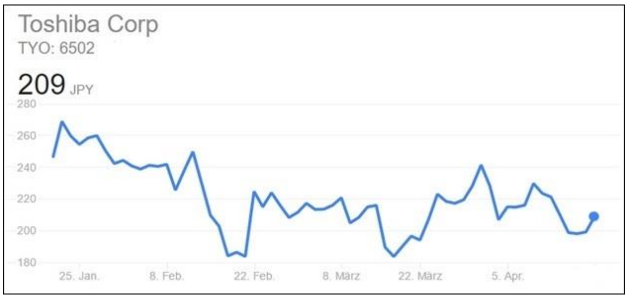
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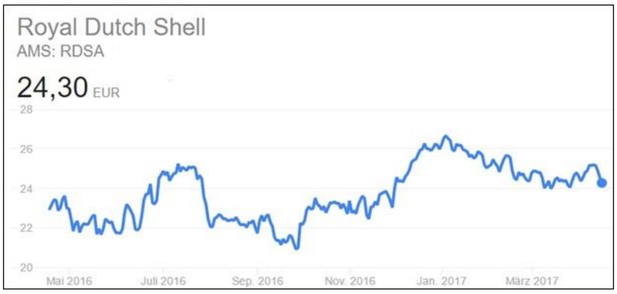
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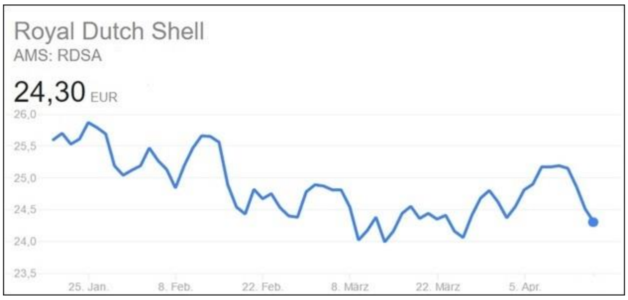
Royal Dutch Shell
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4. Results

A month after the distribution of the surveys, the experimental data is analyzed. It can be underlined that the forecasts do not point in a major optimistic or pessimistic direction. After careful inspection of the data (medians, proportions of de/increase predictions, variances etc.) I notice that the forecasts are firmly based on the charts, as several charts make appear clear forecasting pattern. Furthermore, I assume that no economical turmoil or conjuncture influenced the predictions and as the time frame covering the experiment was not marked by any particular global activity, I consider the right conditions were given to conduct this experiment.

Even though a major political event occurred, namely the French presidential election of Emmanuel Macron, I consider that it does not impact or bias the subjects' forecasting behaviour in any way, not for French firms nor other European firms. And while the election of Donald Trump in the U.S. had sent Dow Jones' index up in the beginning of the year, I do not consider the US politics (nor any politics) to have influenced the forecasting exercise in any way.

Several pattern emerge and recur such as the following of trends and mean reversion and ample differences in predictions stemming from different time frames are found. The findings are grouped in sections, each part consisting of an analysis as well as a short conclusion. As the study consists of a point estimate, the focus lasts more on the emerging forecast pattern that build the heart of the study.

4.1. Trends

Trend following predictions are among the recurring pattern in this study. Their emergence is an example of a heuristic afflicted prediction and the idea that individuals are more likely to follow trends, the stronger they are, is confirmed by the experimental data. Several charts have been used that visibly displayed trends and for those charts, more or less respondents chased the trend, depending on its intensity. This is in line with the statement of De Bondt (1993), arguing that most traders expect trends to continue.

The cases for which charts displayed trends and the proportion of trend following subjects are summarized in Table 1. In this table, trends are denoted "weak", "decent" or "strong". A weak trend does not exceed a price variation of more than 5% over the whole chart while a decent trend exceeds this threshold significantly. Lastly, the difference between a "strong" and a" decent" trend is that the strong trend is cleaner (i.e. less fluctuations, price curve starting significantly closer in the bottom left of the chart ending top right). If a chart displays a trend, the subjects that decide to follow this pattern (e.g. the price has decreased over the last months, the subject predicts further decreases) are denoted Trend "chaser". The number figuring next to "trend chaser" on figures 6-10 is the median prediction among those subjects that followed the trend. Medians are used in order to avoid the influence of outlier.

Trend	**Company**	**Time frame**	**Trend chaser**	**Initial price**	**Overall median prediction**
Upward (weak)	Coca Cola	3-month	61 %	43,48 $	43,98 $
Downward (weak)	Gillette	12-month	64 %	4160,00 ₹	4158,00 ₹
Upward (decent)	Google	12-month	76 %	853,99 $	855,00 $
Upward (decent)	Fujitsu	12-month	74 %	683,00 ¥	685,00 ¥
Upward (strong)	Samsung	12-month	72 %	2'045'000 ₩	2'090'000 ₩

Table 1 : Summary of the trend following predictions

In every case, the trend is followed by a majority of participants (Table 1). For weak trends, less subjects followed the trend than for stronger trends (61 and 64 % compared to 72, 74 and 76%). However, when trends continued in reality, the trend chaser had underestimated the trend. The following charts (fig. 6 to 10) basically show the medians of those who followed the trend and of those who didn't. As before, Trend chasers are those that predict a continuation of the current pattern, where as Non Trend chaser go into the opposite direction. On close examination one notices that the weaker the trend is, the stronger is the deviation from the trend in the Non Trend chaser group. So while the majority still followed the weak trend, a part of the subjects decided that a weak trend is likely failing to continue.

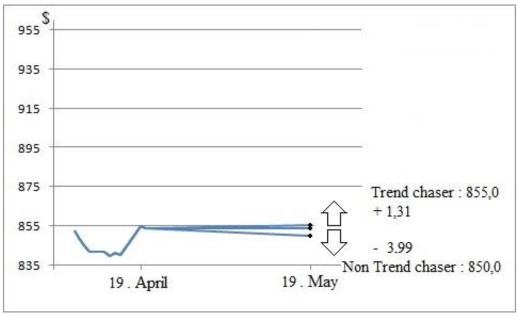

Figure 6 : Google, weak upward trend
Vertical axis : USD Horizontal axis: time

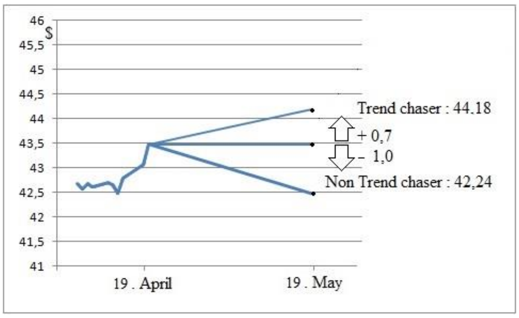

Figure 7 : Coca Cola, weak upward trend
Vertical axis : USD Horizontal axis : time

As can be seen on fig. 6 and 7, for weak trends the Non Trend chaser's predicted mean deviates stronger from the initial price than the Trend chaser's predicted median (i.e. (3,99 > 1,13) and (1 > 0,7)). Regarding more decent trends (fig. 8 and 9), we find the opposite; the Trend chasers predicted median now exceeds the Non Trend chaser's median in terms of deviation intensity from the initial price (i.e. 7,00 > 3,00 ; 60 > 40). This shows that the stronger the trend is, the more subjects, more or less blindly, follow this trend and consider it to continue.

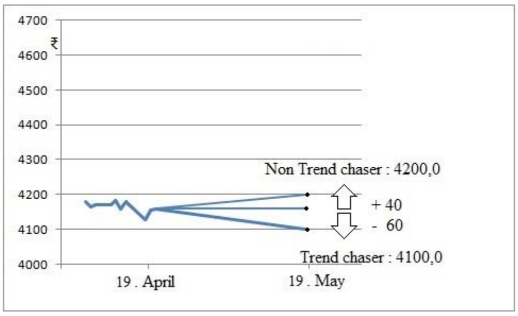

Figure 8 : Fujitsu, decent upward trend
Vertical axis : INR Horizontal axis : time

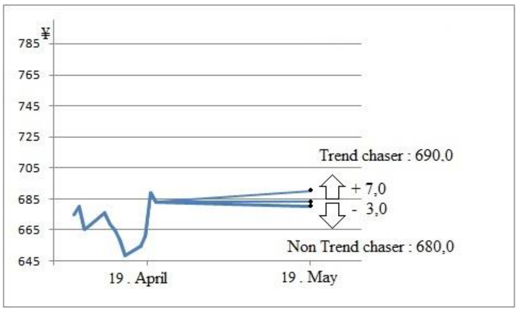

Figure 9 : Gillette, decent downward trend
Vertical axis : JPY Horizontal axis : time

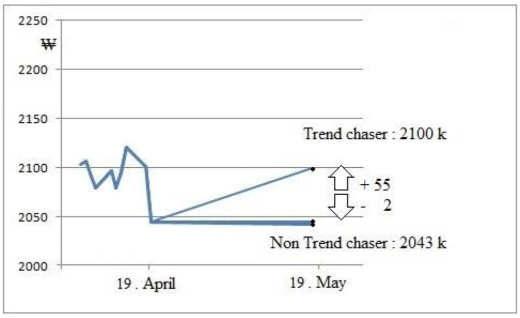

Figure 10 : Samsung, strong upward trend
Vertical axis : KRW Horizontal axis : time

Perhaps the most robust example in this setting is Samsung (fig. 10), where the trend was at its strongest. The Non Trend chaser's median is insignificantly distanced from the initial price, when compared to the Trend chaser's deviation (2'000 KRW compared to 55'000 KRW). Now we found that weak trends result in stronger deviations from the initial price and vice versa, while our strongest trend displays very insignificant deviation from the initial price in the Non Trend chaser group. In order to make this finding more robust, we analyze the charts that do not display trends. Table 2 refers to the median of the group that predicted increases and displays the medians of those who forecasted decreases and computed their median deviation from the initial price in monetary units. For those charts that were genuinely trendless, the intensity of upwards compared to downward deviations are quite equal (i.e.0,7=0,7; 0,89~1,11 ; 40~60 ; 0,5~0,8). Significantly more equal than for charts displaying trends. The absence of trends leads to more diverse and less uniform predictions in both directions. Trendless charts make it harder for subjects to give an intuitive estimation and result in less homogenous predictions, where as trending time series give the subjects something to "anchor" on. The main finding is that, overall, subjects prefer to follow trends, as they consider it to be an appropriate guess. However, those intuition afflicted decisions are without guarantee. The phenomenon of following trends is with what Tversky and Kahneman (1975) call the anchor and representativeness heuristic.

Company	**Period** (months)	**Median of those having predicted an Increase**	**Median of those having predicted a Decrease**	**Upward deviation** (monetary units)	**Downward deviation** (monetary units)
Coca Cola	12	44,18	42,78	+0,70	-0,70
Nike	12	57,00	55,00	+0,89	-1,11
Gillette	3	4200,00	4100,00	+40,00	-60,00
Royal Dutch	3	24,80	23,50	+0,50	-0,80

Table 2 : Medians and deviations for non trending charts

Individuals make use of intuition and heuristics when it comes to decision making and by anchoring on a value, individuals expect a continuation of the pattern of past price changes (De Bondt 1993) and consider the past price changes as representative for future ones. This heuristic is quite common, as a price that has steadily been going up, is considered by most to be likely to continue in absence of major economical turmoil whereas prices that have been decreasing for a while can convince many people to anticipate a further decline. Many of those feedback traders, as De Long *et al.* (1990) calls them, result as a consequence of displayed trends in this experiment.

For instance, since Samsung is a very popular electronics brand that has a variety of products ranging from Smart phones to fridges, most people would consider Samsung to be a lucrative firm. Additionally, a constant and stable upward trend of its stock price pattern since May 2016 has led most (72%) of the respondents to predict a further increase. Similarly, Gillette's stock prices have been decreasing since July 2016. This long term decrease has been taken as being representative for future price movements. However, Gillette's stock prices have broken the downward trend and have increased more than 10% in the last month.

In the case for Gillette, the trend following anticipations were very wrong since its stock prices actually increased. However, Samsung's stock prices increased eventually. Thus, following a trend can be accurate as much as it can be wrong. On the other hand, the cases where no trend could be detected as easily and the form of the stock price chart was rather interesting, the number and intensity of upward and downward forecasts are very close to each other in comparison to the trending charts.

We conclude this part by reconfirming that the tendency to follow trends is quite strong and that the absence of a trend results in forecasts that are spread more widely in both, upward and downward, directions. Hence, charts affect the forecasting exercise significantly and while strong trends result in a high amount of trend followers, stock price charts that display very weak trends result in a considerable part of individuals forecasting future prices that go against the trend to a stronger extent than for trend followers. Weak trends seem to be genuinely perceived as less representative for the pattern to continue and are perceived by some as susceptible to "break" in the opposite direction to an even stronger extent.

The stronger the trend, the stronger is the proportion of trend following predictions. Hence a very strong trend might lead to an awful amount of investors buying the stock and the more investors buy this stock, the more the price is driven away from its intrinsic value, which can create a bubble.

4.2. Mean reversion

Apart from trend following, reversion to the mean is another major pattern which recurs robustly in this paper. According to Keynes (1936), investors assume that market and fundamental value might diverge because of speculative forces, but will ultimately revert to their mean. In addition, a more recent study by Glaser *et al.*(2007b) found that price predictions were often anchored around the mean. This concept is validated by the experimental data as well.

In the experiment, several charts have displayed forms that do not reflect trends but induce those mean reverting expectations. In other words, charts that, instead of displaying trends showed a current price which was noticeably above or below the overall mean, induced subjects to a significant amount of the time to predict a future stock price around its mean. Table 3 summarizes the cases for which mean reversion has been a factor. The denoted "Approximate mean" is a scale interval in the respective chart which represents the stock's displayed overall mean. The median predictions show that the subjects' idea of a price converging towards its mean appears in those charts. I find that the predicted stock price is between the lower and upper border of the approximate stock price average in the respective chart. As the scales do not remain the same with different time frames and the time period has a different length, the mean is perceived differently, and this is reflected in the predictions. The differences between time different charts will be elucidated more closely in part 4.4.

As can be seen on Table 3, the apparent overall mean regarding Shell's stock prices differs when the 3 month period chart is used compared to the 12 month period (i.e. [24,5-25] compared to [22-24]) and both times the median predictions are centred around the respective displayed mean. Hence, the predictions differ and as a consequence we can say once more that stock price forecasting is proven to be influenced to a considerable extent by the form and frame of time series. When no intuitive upward or downward trend can be detected, individuals seem to estimate the mean in case the price is ostensibly above or below it and predict the price moving towards it. Another strong example is Nestlé, in which different apparent stock price averages result in different predictions. The tendency, in which one reverts towards the mean can be considered an anchoring heuristic as well.

Company	Time frame	Approximate mean	Median forecast	Initial	Current
Nestlé	3 month	[74,00 ; 76,00] CHF	74,80 CHF	75,40 CHF	81,55 CHF
Nestlé	12 month	[72,00 ; 74,00] CHF	74,00 CHF	75,40 CHF	81,55 CHF
Google	3 month	[840,00 ; 860,00] $	853,00 $	853,99 $	950,50 $
Shell	3 month	[24,50 ; 25,00] €	24,50 €	24,30 €	24,85 €
Shell	12 month	[23,00 ; 24,00] €	24,00 €		
Deutsche Bank	12 month	[14,00 ; 16,00] €	15,50 €	15,24 €	16,76 €
Toshiba	3 month	[200,00 ; 220,00] ¥	217,00 ¥	209,00 ¥	232,00 ¥
Fujitsu	3 month	[660,00 ; 680,00] ¥	665,00 ¥	683,00 ¥	791,00 ¥
Bayer	3 month	[104,00 ; 106,00] €	105,00 €	105,50 €	116,85 €
Bayer	12 month	[95,00 ; 105,00] €	104,00 €		
Ericsson	3 month	[54,00 ; 56,00] SEK	56,00 SEK	56,85 SEK	58,05 SEK
Ericsson	12 month	[55,00 ; 65,00] SEK	56,50 SEK	56,85 SEK	58,05 SEK

Table 3 : Mean reversion, summary of results

Intuitively, individuals think that it makes sense for the price to fluctuate around the mean and converge towards it. As illustration serves figure 11 which displays Nestlé's 12 month chart. Here the upper and lower boundaries of the approximate average of stock prices are represented by brown bars. As can be seen, the chart of Nestlé (fig. 11) has led most (82%) of the subjects to predict a decrease as the stock price is ostensibly above the prices mean in end of April. Figure 11 counts as well for the rest of the charts in this setting as can be confirmed by Table 3.

Figure 11 : Nestlé,

12 month time frame, average and median prediction

Additionally to median predictions, it is helpful to inspect a dot plot of the predictions to illustrate the frequency of predictions. Referring to Table 5, we can see once more on Figure 12 that the majority of predictions are centred around the mean.

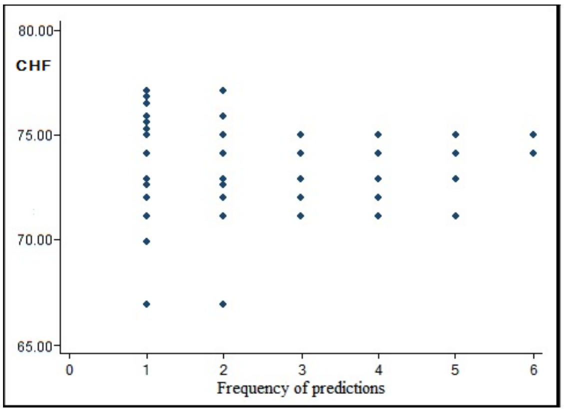

Figure 12 : Dot plot : Predictions of Nestlé's 12 month chart
Horizontal axis : Frequency of predictions
Vertical axis : Swiss Franc

The approximate mean of Nestlé's 12 month stock price lies between 72 and 74, (or if considered broader between 70 and 75) and now it becomes crystal clear that, in terms of median predictions and frequency of predictions the forecasts are majorly anchored around the mean. Figure 11 and 12 do display the same characteristics for the remaining charts that induce mean reversion (Table 3).

We can argue that the reversion to the mean is a phenomenon that recurs heavily and results from an intuitive thinking procedure in which one takes the mean as a reference. It can easily lead individuals to make wrong predictions, since there is no reason for stock prices to converge to their mean in the short term (in the long term however, they do). The direction, the stock price takes in the short and medium term is related to forces such as the interaction between supply and demand of the stock and, as mentioned earlier, is influenced by fundamental and technical factors as well as the market sentiment. The reversion to the mean results from wrong expectations that people have and that result from our bounded rationality in which we use our intuition.

4.3. Volatility charts

Having discussed the major pattern in charts, it is examined how volatility affects the forecasting behaviour.

The results are quite straight forward on this one and show that charts, that display high levels of volatility, result in forecasts in which the proportion of increase predictions and decrease predictions is almost equal. As can be seen on Table 4, when taking the median of the predictions for the respective companies, one immediately notices that they do not differ significantly from the initial price. Those examples point to the fact that if subjects are confronted with high volatility charts, they are less able to make intuitive predictions with ease. Actually, the probability of someone predicting an increase (or a decrease) on such a high volatility chart is almost equal to a coin toss.

Company	**Time Frame**	**Subjects Predicted Increase / Decrease** (in %)	**Initial price**	**Median of predictions**
Gillette	3 month	51 / 49	4160	4170,00
Nike	12 month	53 / 47	56,11	56,20
Nike	3 month	49 / 51	56,11	56,06
Toshiba	12 month	55 / 45	209	207,50

Table 4 : High volatility charts : results

Price charts that display back and forth increases and decreases involve higher uncertainty as to what direction the price is likely to move next. The black dots on Figure 13 show the predictions which reveal to be distributed in near range (initial price 4160,00) with a distribution reaching from a minimum of 3745,00 to 4300,00₹/share.

One can infer that many subjects intuitively take the close scales as help for predictions and anchor on (4100,00 INR and 4200,00 INR) as can be seen on Figure 13. As the medians of predictions approximately equal the initial price, one can see that although volatility is high, and although predictions go in both upward and downward directions, that predictions stay in quite close range. Hence, when subjects are confronted with high volatility charts, many seem to chose the closest displayed scale as prediction.

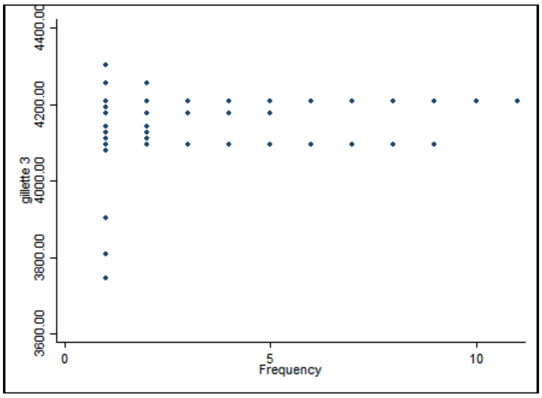

Figure 13 : Dot plot of predictions Gillette (3)

Vertical axis : predictions in INR

Horizontal axis : frequency

As most predictions are 4100 and 4200, the displayed chart's scale influenced the predictions. As the current price skyrocketed to 4699,5 ₹/share, it becomes evident that high volatility charts complicate it a lot for the individuals to make an accurate forecast.

We can conclude that predictions regarding high volatility in charts include higher uncertainty from the subject's point of view and complicate the decision, resulting in more equal proportions of increase and decrease forecasters whose predictions, despite the high past fluctuations, stay in close range to the initial price. Those characteristics recur over and over again in the examples in this setting. For Nike's 12 month time frame for instance, the max. and min. predictions anchor on the next scales (50 and 60), where as a decent amount of predictions in the 3 month period chooses 54 and 58 as prediction, which are the nearest displayed scales in this time frame. Although the grey horizontal lines on the charts had actually been removed for the forecasting exercise, subjects seem still influenced by the displayed scales on the vertical axis.

4.4. Different time frames

It is stated in the literature that there is no agreement about the length of the chart time frame that most investors inspect in order to make predictions (Glaser *et al.*2007b). Including charts with different time periods in the experiment allows to investigate to what extent different time frames affect price predictions. The findings stemming from time frame disparate charts concerns differences in pattern and in scales.

4.4.1 Pattern differences

As discussed in the first part of this paper price charts can, at first sight, differ as much as they can resemble each other when switching time frames (c.f. Figure 4 & 5). Our results show once again that the form of past price movements has a strong influence on the subjects' forecasts. On the one hand, in those cases in which 3 month and 12 month period display similar characteristics, i.e. both trending or both induce mean reversion forecasts, the median predictions largely go in the same direction and do not differ considerably from each other. However, on the other hand, charts whose pattern remarkably differ when different time frames are used result in more contrasting forecasts. In Table 5, the averages of differences in median predictions between the 3-month and 12-month charts are computed. The results indicate that there is a recurring difference in forecasts between charts that differ and charts that resemble. On average, forecasts differ by 1,13% in medians where as the charts expressing different pattern have an average difference of 2,9% for the medians. Basically the similar chart pattern do always have a lower median forecast difference, except for Coca Cola whose difference in medians is significantly higher. On average, however, there is a recurring difference.

Company	**Pattern**	**Difference of medians in %**
Alphabet Inc.	Similar	0,9
Coca Cola	Similar	2,3
Ericsson	Similar	1
Gillette Ltd.	Similar	0,9
Nestlé	Similar	1
Nike	Similar	0,8
Bayer AG	Similar	1
on average		1,13
Deutsche Bank	Different	3,2
Fujitsu Ltd.	Different	3
Samsung Elec.	Different	1,9
Royal Dt. Shell	Different	2,1
Toshiba	Different	4,3
on average		2,9

Table 5 : A comparison between differences

Figure 14 displays an upward trend when considering the twelve month period while showing high volatility in the shorter term. While in the three month period 95% of the subjects forecasted a decrease, only 25% predicted a decrease in the 12 month chart. While the short term induces subjects to revert to the mean, the long term chart leads to trend following.

The inspected time frame and the resulting difference in chart pattern influences the forecasting results solidly. The finding, that charts displaying different pattern due to

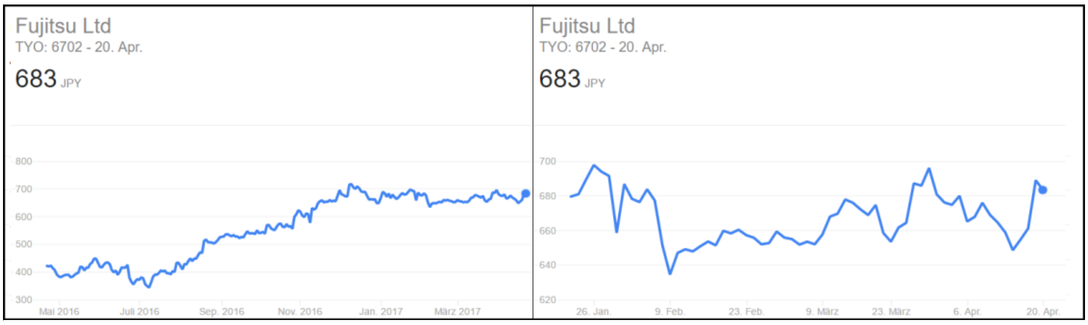

Figure 14 : Fujitsu Ltd. (lhs.) 12 month period, (rhs.) 3 month period
Vertical axis : JPY Horizontal axis : time

different time frames can lead to very divergent forecasts, remains persistent in this paper. We have to underline that the differences in pattern, that result from different time frames, have a strong influence on the forecasts.

Another difference concerns the scale differential regarding charts with different time frames.

4.4.2 Difference in scales

As subjects base their forecasts on the whole displayed time series, the difference in scales (i.e. the fact that 12 month charts' displayed scale interval usually exceeds the 3 month charts scale interval considerably) affects the variance of the forecasts (i.e. the dispersion of the forecasts) to a certain extent. Displaying different time frames can lead to different forecasts and as the survey data demonstrates, the variance of the forecasts that stem from twelve and three month periods does differ. Table 6 summarizes those results.

Considering this table, we can infer that from a more general point of view, the variance of forecasts stemming from longer period charts are larger, or in other words the predictions deviate stronger away from the initial price. In ten out of twelve cases the data confirms this. Statistically however, only for Google, Ericsson and Fujitsu those twelve month period variances exceeded the three month period significantly.

Company	Variance of 3 month period		Variance of 12 month period
Google	340,94	**<**	737,13
Coca Cola	3,26	<	4,01
Ericsson	3,27	**<**	11,86
Gillette	11'827,41	<	15'361,19
Nestlé	5,17	<	5,77
Nike	4,56	<	5,52
Bayer	8,45	<	12,24
Deutsche Bank	3,55	>	1,54
Fujitsu	635,61	**<**	1213,83
Samsung	1'957'255'255,26	<	29'080'618'956,16
Shell	2,48	>	1,57

Table 6 : A comparison of the variances

Hence, the more noticeably different the scale differential is between two charts displaying different time frames, the stronger will be the difference in variance of forecasts. Deutsche Bank and Shell do not follow this concept. While for Deutsche Bank, the explanation might be that the three month chart displays a scale interval that is almost 60% of the twelve month chart's scale, (most 3 month charts display around 30% of the 12 month chart's scale), I find that for Shell the differences in variances come from the fact that its 3 month chart displays massive volatility while the 12 month chart clearly results in a majority of subjects following their reversion to the mean heuristic and predicting a price more uniformly.

When calculating the proportion of the twelve month charts' scale interval, that the three month chart actually expresses in terms of percentage, I notice that those variances that are on the edge of significantly exceeding the three month chart's variance display a scale that is around 30% as big as the scale of the larger time frame. As Ericsson's and Fujitsu's three month chart display respectively 25% and 16% of the twelve month charts' total vertical scale, there is a significant difference in variances. For Google the smaller time frame displays 32% of the larger time frame's scale, however the difference in variance is significant as one time frame results in mean reversion while the second time frame leads to trend following.

From a general point of view, the reason for why those variance differences recur can be also explained by the difference in scales as individuals overestimate the range of possible prices given by the scale of the chart, or "anchor" on the scale, overestimating the range of possible prices in the 12 month chart compared to the 3 month chart. When making forecasts intuitively, one takes the scale into account when estimating and thus the scales influence the predictions.

As illustration, the three month chart of Fujitsu's stock prices (fig. 15) has a vertical scale that goes from 620 to700 JPY while the twelve month chart's scale ranges from 300 to 800 JPY. The dispersion of the forecasts becomes almost exactly twice as large for the 12 month chart prediction, as can be seen on Table 7.

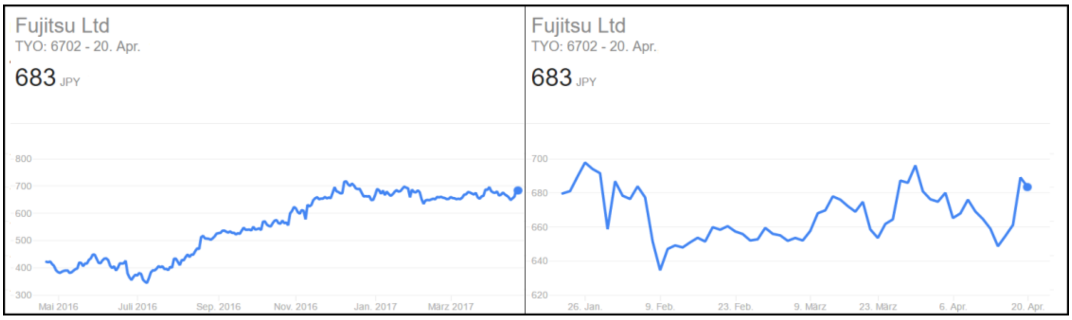

Figure 15 : Fujitsu Ltd. (lhs.) 12 month period, (rhs.) 3 month period
Vertical axis : JPY Horizontal axis : time

Therefore we can conclude that the larger the time frame that subjects inspect prior to making a prediction, the larger the forecasts will be dispersed from each other and vice versa. Hence, the difference in pattern, but also the differences in scales impact the price forecasts to an ample extent.

5. Summary

Overall, the study has presented the forecasting pattern that have resulted from two dozens of price paths and has revealed the impact that charts have on stock price forecasts.

Displayed trends result more or less in trend following predictions depending on the intensity of the trend. When no clear trend can be detected, but the price is obviously above or below the chart's mean induces subjects to make a mean reverting prediction. In those cases when none of the just mentioned pattern are displayed and volatility is high, the proportions of increase and decrease forecasters resemble a coin toss scoreboard and predictions anchor on the next displayed scales (e.g. most predictions chose on 4100 and 4200 INR for Gillette etc). Charts that display different time frames have two impacts. First, the form and allure can be very different when changing time frames and hence can, for instance, lead to mean reversion in the short time period while inducing trend following in the longer term. Second, the scale differential results in variously dispersed predictions. As the larger time frame is 4 times as large as the shorter time frame (12months = 4· 3 months), the range of potential future prices can be easily underestimated in the short term chart compared to the longer term chart ([620-700] compared to [300-800]).

When trend following revealed to have the right direction, trends had been underestimated. Regarding the mean reversion inducing charts, the predictions are even less accurate. Almost every single time subjects have reverted to the mean, this was a prediction in the wrong direction (table 3). However, those results could have as well been the opposite, as the data is gathered from a point estimate.

While authors such as Keynes (1936) state that prices will ultimately converge towards their mean in the long term, the probability for the price converging towards its mean in the next 30 days during forecasting exercise is very low and therefore the reversion to the mean becomes less relevant. All-in-all price paths affect the forecasting exercise tremendously as different time frames from a same company can result in very different predictions and those can be dispersed more or less widely depending on the scale differential between the both frames.

The major component in this paper here is the anchoring and representativeness heuristic, which is present in trend following as well as mean reversion and leads to contrasting forecasts resulting from different scale size and pattern. As charts have revealed to have a considerable impact on stock price forecasting, we should underline that one should pay attention when making a price prediction with the sole use of charts, because the sole form of time series does not have enough information to make accurate forecasts consistently. Following trends and reverting to the mean is, as mentioned, linked to a same heuristic in which individuals take past price movements representative for future ones.

What does this analysis tell us about how to make stock price forecasts? As we have seen, pattern such as trends can be misguiding. Indications of future, harsh deviations from a stock price's trend might be able to be detected through fundamental analysis but remain yet undetected in the displayed price path. Our bounded rationality, which Gigerenzer and Selten (2002) consider as adaptive toolbox, helps us to make decisions that appear accurate and that we consider as realistic. Intuition is a handy tool that we use to make decisions, but regarding stock price forecasting this aid has no guarantee. A good way to forecast stock prices might be adding other procedures to the chart investigation. By adding fundamental analysis to technical analysis, as many do, both complementary methods are likely to increase the forecasting performance.

This paper has been based on experimental data stemming from undergraduate students, and although finance was not their primary field of study, the subjects for my study have been chosen in a way that a certain economical background was present and thinking as well as predicting with earnestness were assured. While my subjects might not represent the thinking of an experienced broker, I believe, referring to earlier findings from Glaser *et al.*(2007b) and Deaves *et al.*(2010), that my subjects have all been suitable for the experiment. However, replicating the study with experienced brokers, could have changed the results as their experience might combat intuition and whim. Hence choosing students might be a small limitation in this study, but guaranteed a decent amount of answered surveys as finding suitable students is easier than finding brokers that are willing to take part in this paper. Also, as the amount of answers collected per chart did not exceed 50 subjects and as the study consists of a point estimate, the results have to be interpreted cautiously. Also, as we have been referring to bounded rationality and heuristics, I cannot exclude if there was any framing effects in the way the questions were posed in the survey. However, I am convinced that no framing effects have been present as the instructions were very straight forward.

Several possible extensions come to mind as well. Instead of asking for precise forecasts on one day one could additionally ask for an interval or for several future prices on different dates so as to find out how the subject intends to price to evolve - actually there are many possible designs which would allow to capture more than has been done in this analysis. Also, it would have been interesting to see to what extent forecasts differ, if same subjects are chosen again one month after their first forecasts in order to see how subjects cope with their earlier intuition afflicted and maybe wrong decision making and how this learning would affect the above mentioned forecast pattern in a second setting. Those are, however, just a few possible extensions that might remain interesting avenues for further research.

5.1 Conclusion

In conclusion, this paper has revealed that price charts affect stock price behaviour tremendously and the major recurrent pattern have been investigated. Also, how the use of different time frames, when attempting to forecast prices, affects the predictions has revealed to be of major impact. This paper has shown that when we have to make an educated guess and predict future stock price using time series of past ones, our decision making processes are largely influenced by our bounded rationality and thus we make use of the anchor and representativeness heuristic (Tversky and Kahneman 1975). Those heuristic and intuition attached decisions can easily be erroneous and to what extent individuals can be educated in order to combat their heuristics and act more rational is just another possible path for further experimentation and exploration.

6. Literature

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