VERSLAS: TEORIJA IR PRAKTIKA
BUSINESS: THEORY AND PRACTICE
ISSN 1648-0627 print / ISSN 1822-4202 online

2013 14(2): 166–176
doi:10.3846/btp.2013.18

MARKET PRICE FORECASTING AND PROFITABILITY – HOW TO TAME MRANDOM WALK?

Bohumil Stádník

The University of Economics in Prague, Faculty of Finance and Accounting, W. Churchill Sq. 4, 130 67 Prague 3, Czech Republic
E-mail: bohumil.stadnik@email.cz

Received 22 Jan. 2013; accepted 31 Mar. 2013

Abstract. Directional forecasting of a future market price development of liquid investment instruments is the focus of interest of investment companies, individual investors, banks and other financial market participants. This problematic has still not been fully answered because the market price development is a process which is very close to a random walk and appropriate models are still under the discussion. The opportunities can be used for the better prediction, their usage for profit making, quantification and also their discussion according to the current financial market models (models with the direction or the volatility dependence) is the core of the paper. The purpose of this research is also to simplify the whole situation for the practitioners due to the complicated theoretical background of this financial market topic.

Keywords: market price prediction opportunities, price directional forecasting, Dynamic Financial Market Model, random walk, non-normal distribution, feedback on financial market, volatility dependence, directional dependence.

JEL Classification: G10, G12, G14, G17.

Introduction

The main contribution of this financial engineering study is to complexly assess opportunities of the market price directional forecasting of liquid investment instruments and also discuss how to use the possible forecasting improvement for a financial profit making. In this context we identify and discuss the price directional dependency on the past, which is the core of each forecasting, discuss its quantification and also complexly describe the economic situations offering the better directional forecasting. Consequently we discuss and try to quantify the profit realizing opportunities which are logically arising from the directional dependence which has been possibly found. The purpose of this research is also to simplify the difficulties for practitioners due to the complicated theoretical background of this financial market topic. Some effects within the financial markets which are related to the directional dependence can be explained using both the directional and the volatility dependence models. As these models has the different impact on forecasting we also discuss the validity of the models which use the volatility dependence on one hand and the models using the market price directional dependence on the other hand. For such purpose we do the complex simulation of empirically measured financial markets distributions of returns with the usage of the volatility dependence and then study its possible economic interpretation.

While many papers focusing on the construction of optimal portfolio (Markowitz 1952; Sharpe 1963) in this study we try to resolve the problematic of market price directional forecasting of the individual asset. There are many studies on the topic of future price directional dependence. We meet many interesting detailed works, case studies or forecasting tools in the area of the development direction dependence (Fama 1966; Henriksson, Merton 1981; Anatolyev, Gerko 2005; study of the connection of liquidity and market crashes done by Huang, Wang 2010; Trešl, Blatná 2007). Some works are connected to the prediction of business cycles (Pesaran, Timmermann 1995; Birchenhall, Osborn, Sensier 2001; Lillo, Farmer 2004; "Predicting UK Business Cycle Regimes"; Dzikevičius, Vetrov 2012; etc.) or direction of change ideas (Rydberg, Shephard 1999). Market price directional dependence is the base for Technical Analysis which is trying to predict future market price development using geometric shapes inside the historical price charts. We can consider Technical Analysis to be the prediction tool, but its benefit is still under the discussion. Some works indicates that several technical indicators do provide a little forecasting improvement and may have some practical value (Lo, Mamaysky, Wang 2000). The price directional dependence is also taking place in the primary feedback process according to behavioral finance concept where upward trend is more likely to be followed by another upward movement (Schiller, "From Efficient Markets Theory to Behavioral Finance" 2003) or in some other researches like for example momentum studies (Stankevičienė, Gembickaja 2012, etc.), short term trend trading strategy in futures market based on chart pattern recognition (Masteika, Rutkauskas 2012), forecasting models (Wei, Yoshiteru, Shou-Yang 2005), development of the decisions strategy in capital and money markets (Rutkauskas, Miečinskiene, Stasytyte 2008). We have to mention also works of Larrain (1991), who states that long term memory exists inside the financial market or other similar works of Hsieh (1991), Peters (1989) which are focusing mainly on measurement of probability diversions from normality, also using Hurst coefficient, but these theories are not solving in details their economic explanation using processes and elements existed within the real financial market.

The Dynamic Financial Model (Stádník 2011) is solving completely the problematic of the direction dependence. The model is the comprehensive one, putting great emphasis on the realistic economic interpretation and we are going to use mainly this model for answering "forecasting" questions in this research. The initial part of this study is the definition and explanation of a prediction possibility during an investment process and its quantification. The next part of the paper is a discussion of logic conclusions for the prediction possibilities that we can deduce from financial market returns distributions characteristics, we have obtained from the empirical measurements. As the distribution is not a Gaussian one, it means the process behind is not one independent random walk with certain average length of step, but we have also reason to expect some rules inside the system, for example in a choosing of the price development direction. Then we do the detail analysis of the sequence of processes from which is the market price development compounded. The sequence involves processes like the next future step direction probability determination, the time delay and the step creation. In the fourth part we define situations with better prediction possibilities according to expected causalities and the time delays in the sequence of the processes. We also discuss them according to the Dynamic Financial Market Model and the models with volatility dependence.

1. Quantification of a Forecasting Advantage

Quantification of a forecasting advantage is resulting from the following example. If we do the sequence of investments (for example on one day basis –when each day in the morning we open the long or the short speculative position and in the evening we close the position) and the probability of each day profit = 52%, loss = 48% then our profit/loss (P/L) development is the non-symmetric binomial process with the probability of the next step direction = 52% for the up direction and 48% for the down direction. Our forecasting advantage, which we are in this case also able to use for profit making, is defined to be 2% above 50% (52% – 50% = 2%). The question is then: "Has such advantage its practical value?" From the theory of probability it is obvious that even if the forecasting advantage is positive, we cannot be sure about the positive aggregate profit in the future. There is an example of a case of possible negative development with 2% forecasting advantage in the figure 1.

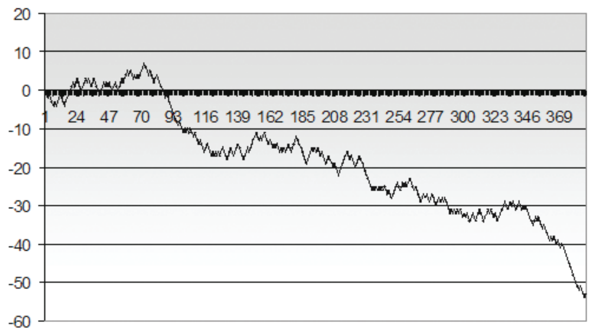

Fig. 1. Possible negative profit/loss development for an investor with a forecasting advantage 2%

With an increasing number of investments the percentage deviation from its average value is decreasing according to the law of large numbers (the average of the results obtained from a large number of trials should tend to the expected value while more trials are performed). By the way of example: if the number of particular investments is 100 and the probability of profit/loss is 60/40 then 60% of investments will be of the positive P/L (in average) and the average deviation from the value is +/– 2.4%. While increasing the number of investments to 1000 then the average deviation is decreasing to +/– 0.76%. If we increase the number of investments to 10 000 the average deviation is +/– 0.24%.

2. Logic of Assessment of Forecasting Possibilities According to the Returns Distributions

In the case of the market price development of many liquid financial instruments we observe not Gaussian distribution of returns with a positive kurtosis which is characterized by the fat tails at the borders and the sharpness in the mid-area of the distribution. These distributions also exhibit skewness and extreme values. Good example is the daily returns probability distribution of S&P 500 in the figure 2. As the distribution is not the Gaussian one, the process behind cannot be an independent random walk but we have also reason to expect some rule inside the market, for example in a choose of the direction of a price development. Summary of the logical conclusion we obtain from the shape of the distribution:

- If a market price development process is an independent random walk (probability of each step direction is independent on the past, length of each step is also independent and it has certain average step length) probability distribution is of a Gaussian type.
- If the process is not an independent random walk, probability may or does not have to be Gaussian. Some causal processes can simulate Gaussian distribution.
- If a probability distribution is Gaussian then the process behind may be an independent random walk but may be also some causal process which simulates Gaussian distribution.
- If the probability distribution is not Gaussian then the process behind cannot be an independent random walk.

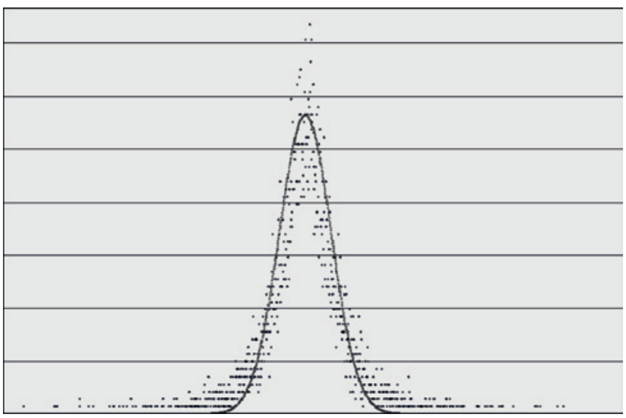

Fig. 2. Daily returns (1970–2010) of S&P500 (dots), normal curve (line)

3. Market Price Development Process Details

According to the all accepted financial markets models the market price development is compounded from a set of steps. The smallest step is the minimum price tick, which is given by the certain market rule to the each traded investment instrument. According to the efficient market theory we recognize "economic news" steps which are generated by incoming relevant economic news. As the economic news is unpredictable and independent (in this theory), we assume Gaussian character of these steps. The sequence of more steps creates an independent random walk with the certain average step length and thus its probability distribution is of a Gaussian type. According to the Dynamic Financial Market model (Stádník 2011) we recognize the "economic news" steps and also the "primary" steps with the length equals to the minimum price tick. "Primary" development is active also in the time period without incoming of any economic news. A sequence of "primary" steps is a Gaussian type random process if there is not any feedback process triggered. If there is a feedback process active, probability distribution does not have to be Gaussian.

According to the empirical evidence we can resolve a step creation process into a certain sequence. The sequence is the same for the both "primary" and "economic news" steps and it can be resolved in the following: **direction probability determination →time delay → step creation finish**. Value of the determined probability of up or down direction of the next "primary" step can be 50% in the case of the symmetric independent random walk of "primary" steps or can differ from 50% due to for example the feedbacks. The probability value is not usually commonly known value, its finding can be difficult but it is built inside the development process. We can divide probabilities into two groups:

- primary independent random process with the constant up/down probability,
- dynamically changing probability.

If the probability of the next price step direction is dynamically changing we can expect its dependency on factors preceding probability determination. Between the time when the probability is set and the time when the step is done there is a certain time delay. Value of determined probability of the next direction of an "economic news" step is given by content of incoming relevant economic news. The delay has variable length which for "economic news" depends on how quickly the market reacts. We recognize:

- Quick step (short or minimal time delay) without significant trading volumes, probability of next price step direction up/down is much higher than 50%. This step has usually the form of a price gap between its beginning and end.
- Slow step (longer time delay) with significant trading volumes, probability of the next price step direction is not significantly higher than 50%. Final step is one step or the sequence of primary steps, where each has probability higher than 50%.

4. Situations with a Better Forecasting and Hidden Rule

If we are able to determine the probability of a future price step direction according to some dependence and its value is higher than 50% then the arising question is if we are able to use such advantage for financial profit realizing. According to the chapter 2 we can state that the certain forecasting advantage allows realizing profit during the sequence of repeating investments with the positive average value and with the P/L deviation which is decreasing in percentage while number of the repetitions is increasing. The other question is if we are technically able to open long/short speculative position (to start an investment). If the determined probability is hidden for some other market participants we are probably able to open the position. However if the determined probability is commonly known we can logically expect immediate adjustment of the market price without trading volumes (price gap) and thus the chances to open position are low. The special case is the situation when the determined probability is commonly known but there is a certain delay between the determination and the moment when the step creation is finished (low efficiency market). We can summarize the conditions necessary to increase our profit realizing probability above 50%:

- the value of a probability must be higher than 50%
- the rule or mechanism which determines its value must be hidden or partly hidden for other market participants or there must be certain delay between the moment of the probability determination and the moment when the step creation has been finished
- the value of probability must cover transaction costs

Within the meaning of the chapter 2 and the law of large numbers it is also important if we can repeat the investments. According to the conditions above we are able to define better forecasting and profit realizing situations:

- "primary" step direction dependency on the past has been found,
- "economic news" step direction dependency on the past has been found,
- low market efficiency has been found,
- chance to make the better estimation for future economic news content than an average expectation is, has been found,
- "volatility" dependence has been found,
- price manipulations are used for pushing of market price,
- insider trading is used to predict the future price development.

5. "Primary steps" Dependency – , the Direction and the Volatility dependence Comparison

Let's discuss now the possibilities to simulate mentioned departures from normality (chapter 3) to asses if the deviations from normality are caused by the volatility or by the directional dependence. Our aim is to create probability distribution according to the figure 2 and assess economic interpretation of such simulation. Required distribution exhibits leptokurtic feature (characterized by fat tails at the borders and sharpness in the central area), extreme values and also skewness (required distribution). Adequate normal distribution is displayed with the line in the figure 2. To be consistent with the chapter 3 we can use directional dependence, volatility dependence or the combination of both for the simulation.

For the directional dependence we consider usage of the Dynamic Financial Market model, which expects possibility of dependence of future price development on the past. The model uses system of feedbacks (including technical analysis, trend stabilizing, price inertia, trading techniques, different up/down movements dynamic, market price manipulations, market regulations) which helps to create abnormalities (using dynamical changes of next "primary" step direction probability) in the distribution and basically assumes that directional dependency exists**.** Idea of feedback processes is based on the observations that traders, investors and other market participants don't only watch present or historical data but according to them they are also placing buy or sell orders and thus influence future development. There is a feedback in the financial markets which also influences a future price development and cause the future direction dependence. The most usual examples are traders who use technical analysis. In the model we work with the feedback processes regardless if they help to realize profit or not. The Model also expects mix of random processes ("primary steps" and "information steps") as a final result. Both effects cause not Gaussian (normal) observations in probability distributions. Dynamic Financial Market Model offers market price dependence which is readable from returns probability distribution. One of the key factors is price inertia feedback. The price inertia is a basic negative feedback which helps to keep price to be unchanged and which is responsible for sharpness in the distribution. Feedback works in all periods of time as a minute, hour or day. If there is not any economic news, primary random walk is forced by traders towards the level which is adequate to the previous economic news level or to the other levels. Simulated realistic distribution using Dynamic Financial Market Model is in the figure 3.

Empirical tests of the price inertia feedback on US Stock Market according to the model have supported its existence (Stádník 2012). Empirically obtained probability of a future price development direction varies approximately from 50%

to 52% (50.04–51.99%). Back tests were done on approximately 2500 US stocks over 10 years time period. These values of a deformed probability of future market price development direction due to the price inertia feedback are in good accordance with the values obtained from the simulation. Similar tests were done on Euro Bund Future on daily basis (1980–2012) and measured probability of the direction to the previous closing price is approximately 51.29%. We can conclude that the short-term dependency has been confirmed.

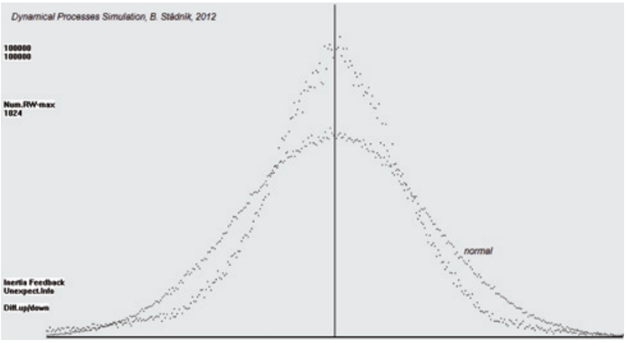

Fig. 3. S&P500 distribution simulation-probability of a step direction changes from 50.00 to 50.76% in the border area, from 50.00 to 50.24% in the mid area of the distribution

Dynamic Financial Market Model offers also other feedbacks connected for example with momentum of the development and which is represented by trend stabilizer feedback in the model. In this case we can consider that determined probability is hidden which allows us to open appropriate speculative position. The question is about covering of transaction costs as the determined probability is not significantly higher than 50%.

The volatility dependence is covered by a wide range of models. Buckley has used in his study (Buckley *et al.* 2008) the Gaussian mixture distribution. Gaussian mixture has acceptable interpretation: financial market performs in two regimes with high and low volatility. Gaussian mixture can model many departured distributions which depend on the probability of both regimes and their parameters. If the latent regimes have a Markov law of motion, the mixture is then a hidden Markov model (Baum, Petrie 1966), which is also known as the Markov regime switching model. There are many extensions of Markov switching model (Krolzig 1997; etc.) Other famous works in this area were done by Bollerslev (1986), GARCH process; Campbell, Hentschel (1992); Engle (1990, 1995), ARCH process; Diebold, Lopez (1995); Jondeau, Rockinger (2003) some new research by Witzany (2013). While GARCH, ARCH and others stochastic volatility models propose statistical constructions based on volatility clustering in financial time series, they do not provide any economic explanation. The economic explanation of volatility clustering is not easy. The initial idea was the competition between numerous trading strategies but complex simulation does not allow confirming this mechanism as being responsible for volatility clustering (Cont 2005). Some economic works contains also examples where switching of economic agents between two behavioral patterns leads to large volatility. In the context of financial markets, these patterns can be recognized as trading rules and the resulting fluctuations as large movements in the market price (supporting heavy tails). Lux and Marchesi (2000), study an agent-based model in which heavy tails of asset returns and volatility clustering can arise from switching of market participants between fundamentalist and chartist behavior. Fundamentalists expect that the price follows the fundamental value. Traders using technical analysis try to identify price trends or other patterns and evaluate their investments using historical development, while fundamentalists evaluate their investment opportunity according to the difference between the market price and the fundamental valuation. According to Lux-Marchesi model the market price development follows Gaussian random walk till the moment when some chart trades using certain techniques surpasses a certain critical value. At this moment a volatility outbreak appears. This process finally leads to volatility clustering. According to Cont (2005) the origin of volatility clustering can be also caused by threshold response of investors to news arrivals.

6. Volatility Dependence – Simulation and Its Economic Explanation

In this chapter we try to identify problems with economic explanation while using models with volatility dependence and so try to contribute to the discussion above (chapter 6).

Models with a changing volatility can be divided according to the reason of volatility change:

- changing of a price step length,
- changing of an activity during a trading period,
- combination of both reasons.

6.1. Volatility Dependence – Models with Changing Step Length and Their Interpretation

If we model abnormalities in a probability distribution using volatility dependence, we can logically assume mix of more particular processes (more periods with a different volatility, volatility clustering). We consider that the price development consists from many different steps, but the steps with similar length always appear in one sequence. Thus we have different sequences of steps, whereas each sequence consists from steps with very similar length.

There are two different sequences of steps in the figure 4 which are involved in the time period for which is the probability distribution constructed. Resulting distribution is then the mix of two probability distributions. Each of them can be in the first point of view considered to be a Gaussian one and the steps inside the period follow an independent symmetric random walk process.

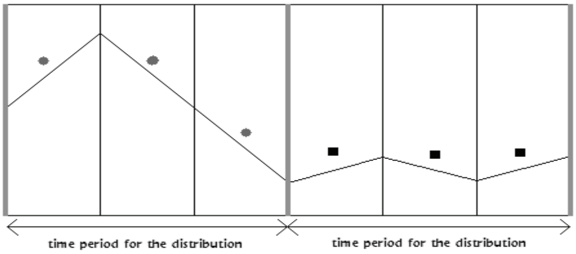

Fig. 4. Model with changing step length

In the figure 5 there is a development which does not consist of two different sequences, but both sequences are the same. Resulting probability distribution with a Gaussian property is compounded from two different steps and the process is not the same as the mix of the distributions.

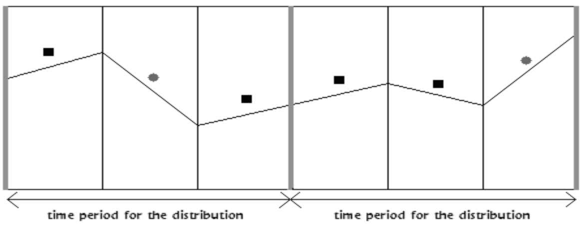

Fig. 5. Model with changing step length

If we simulate (using Monte Carlo approach) the development style in the figure 4 we can obtain, under the certain conditions, the required distribution (figure 2) but the development according to the figure 5 does not allow this. Certain conditions coming-out from the fact, that if we modeling required distribution from the two sequences of different steps size, we can obtain distribution according to figure 6 or 7 which are not required.

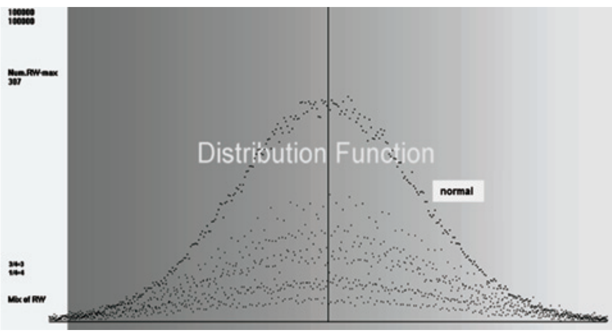

Fig. 6. Simulated probability distribution in the model with changing step length

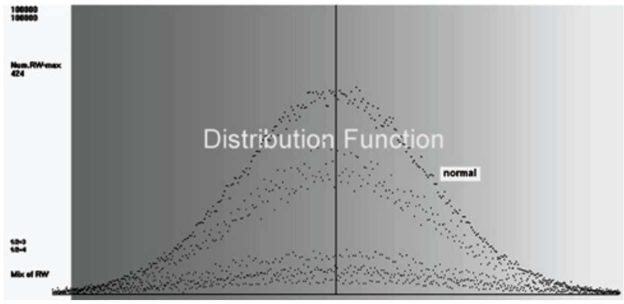

Fig. 7. Simulated probability distribution in the model with changing step length

We have to use such two sequences when longer step from the first one can be compounded of the shorter steps of the second sequence. Then we can create the required distribution as it is shown in the figure 8 and which is in accordance with the empirical distribution in the figure 2.

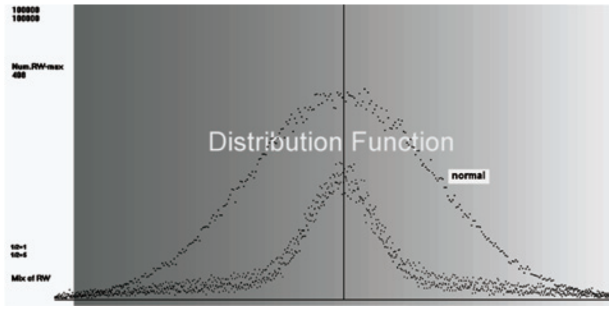

Fig. 8. Simulated probability distribution in the model with changing step length

In case of a mix of great number of different sequences we may obtain probability distribution according to figure 9, which is also not required.

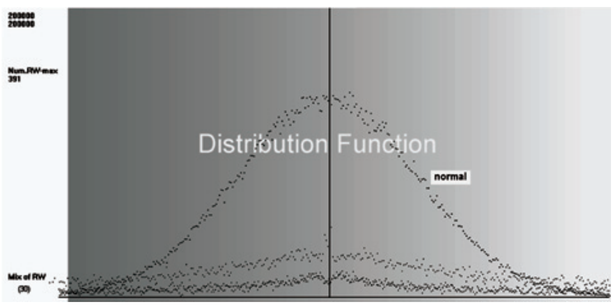

Fig. 9. Simulated probability distribution in the model with changing step length

Figures 6–10 are also the results of Monte Carlo simulations of the described financial market situations. Each simulation is based on 100 000 simulated developments and the each development is consisted of 900 price steps, which is in accordance with the financial market empirical observations. Remarkable is that the distributions according to figures 6, 7, 9 are not commonly observed but we have to suppose that in the case of empirical distributions according to figure 2 (mainly in the case of the mid-area of the distribution) is possible to consider such mix of sequences where longer steps cannot be compounded from shorter ones.

Possible economic interpretation of the process according to the figure 4 which leads to the distribution in the figure 8 is alternation of the two different sequences when the first sequence is primary random walk (as we considering only volatility dependency primary random walk is without feedbacks). Primary random walk is consisted of the steps with the minimum possible size which is given by certain financial market regulations. For example in case of EUREX Euro Bund Future the minimum size of a price increment is 0.01 of a percentage point. Let's say that minimum size of a price increment is 1 market tick. The second sequence could be a sequence of "economic news" steps. "Economic news" steps are always compounded from the minimum size market ticks. Compounding of "economic news" steps from more minimum market ticks avoids obtaining unrealistic probability distributions according to figures 6, 7, 9 where we do a mix of distributions of shorter steps and longer steps which cannot be compounded. The economic explanation problem is that in this case the "economic news" steps should be approximately of the same step length, other vice we simulate cases in the figures 6, 7, 9. The other problem is that on real financial market we usually observe not a mix of these two processes but compounding which is adequate to the situation in the figure 5 and not to the figure 4 and thus we obtain a Gaussian distribution which is not required. In the first point of view we can model required probability distribution using changing step length, but under the certain conditions:

- The size of steps cannot be in independently distributed but we have to consider more regimes with lower and higher volatility (volatility clustering) and longer steps must be always compounded from shorter steps.

  In economic explanation we have to deal with following problems:

- It seems to be very unlikely that the volatility (size of price steps) of each regime can be compounded from volatility (size of price steps) of other regimes.
- Volatility clustering has difficult economic explanation (chapter 6).
- We have economic reason to expect that inside each of the regimes the steps are independently distributed but during empirical measurements we cannot separate more Gaussian distributions to do a mix. All the measured distributions on daily bases on different groups of days are not Gaussian.
- We do not have economic explanation for volatility clustering in very short time intervals where we also do measure not Gaussian distributions and where is no volatility change during the time period.

6.2. Models with Changing Activity and Their Interpretation

Changing activity means for our purposes the situation when we consider different total number of steps during the time period for which we construct the probability distribution. To model required distribution we model two different activities during a time period for the distribution. Modeled distribution is in the figure 10. In case that number of different activities increases the model distribution results into Gaussian distribution which is not required.

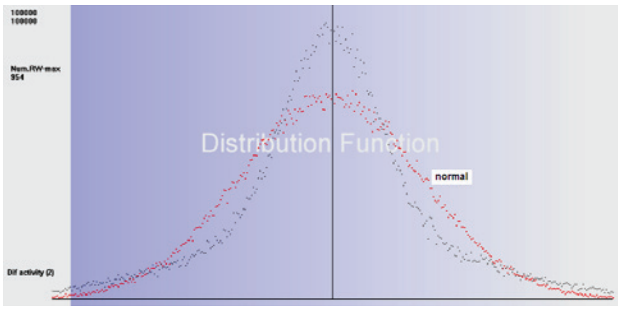

Fig. 10. Simulated distribution in the model with changing activity

We assume that higher activity on financial market arising from the higher frequency of incoming market orders during observed time period. Higher frequency of incoming orders causes higher number of steps in the development. In case of a real financial market we expect that activity varies around certain average value and situation is more close to the Gaussian distribution. This is why the modeled distribution according to figure 10 has very difficult economic explanation. In the first point of view we cannot consider changing activity to be a reason for required distribution.

6.3. Conclusion on Models Using the Volatility Dependence

If we model abnormalities in a probability distribution using volatility dependence, we can logically assume mix of more random processes (more periods with a different volatility) and the volatility dependence in this case means that price movements must respect the period volatility and the size of price movements is not sequencing independently. In this case we explain abnormalities without existing directional dependency. Volatility Dependence basically doesn't support possibility of a market price forecasting. If we prove that Dynamic Financial Market Model is correct and models with volatility dependency are not correct then we can be sure about existed directional dependency in the development which causes departures from normality in the distribution. The problematic question is if the volatility clustering (marked in the figure 11 as the areas with the higher volatility) which can be observed on real financial markets is caused by changing activity (approximately in two levels) or by changing of the length of price steps (approximately in two levels of activity) or by a pure random walk or if it is caused by a combination of more factors. This is difficult to recognize. Anyway we can state that models using volatility dependency have difficult economic explanation.

Fig. 11. Volatility clustering, source: Bloomberg

7. Other Situations Improving Directional Forecasting

Economic News Dependency – If we consider that all the expectations and also all the relevant economic news are built in the market price (average expectation is built), then the content of next economic news is unpredictable and so the probability of caused step direction up/down is 50/50%. The question is then about independency of incoming economic news. This question is still opened. Some market participants believe that "bad" news is more likely to be followed by another "bad news" and so the distribution of economic news is not Gaussian. In this case we can consider that determined probability is hidden (within the meaning of chapter 5) which allows us to open appropriate speculative position. If the probability after the sequence of "bad" news is determined we can expect also a certain delay to the next expected "bad news". The delay also supports possibility of the speculative position opening. Clustering of news is connected to the volatility dependency but it doesn't help to predict future direction.

Better Estimation for Future Economic News Content – Some analytical methods may allow more correct prediction of the content of the future economic news than is an average expectation which should be built in the market price. This is the case of for example core statistical economic data (such as CPI, PPI, etc.) We would be able then predict more correctly the future step direction which is created just after the economic news is released. This practice is also similar to the situation when we know the result of tossing a coin in advance. In this case we can consider that determined probability is hidden and we can also expect a certain delay. Both allow us to open appropriate speculative position. The situation does not have to affect price/yield probability distribution.

Volatility Dependency – This dependency helps to increase forecasting chances for instruments which market price depends on volatility (for example options). The situation corresponds to the models with volatility dependence and their impact on price/yield probability distribution. In this case we can consider that determined probability is hidden which allows us to open appropriate speculative position.

Market price manipulations – If a manipulator use buy/sell orders to push up/down market price then his forecasting advantage is probably higher than 50%. Manipulations are basically illegal but in some cases legal (for example central banks currency interventions). In this case we can consider that determined probability is hidden which allows us to open appropriate speculative position. The situation does not have to affect price/yield probability distribution.

Insider trading – This illegal practice helps to predict a content of incoming economic news. The situation does not influence probability distribution in general. In this case we can consider that determined probability is hidden and we can also expect certain delay between obtaining insider information and the step creation finishing. Both allow us to open appropriate speculative position.

Low Efficiency – Low efficiency can be compared to the situation when after a toss a coin we have to wait certain time to finish the price step. During this delay we can open the speculative position and participate on the profit realizing. In this case we can consider that determined probability is not hidden but the delay allows us to open appropriate speculative position. The reaction of a low efficient financial market is slow but in result "economic news" steps can generate random walk with a Gaussian distribution.

Summary of all the situations with the better forecasting opportunities is in the table 1.

Conclusion

In this financial engineering study we have defined and summarized the primary principals of our approach to the market price directional forecasting and its usage for the

Table 1. Summary of profitability of financial market situations

situation	determ.	delay	hidden	cost	profitable
	value		rule	covering	
primary steps dependency	>50%	no	yes	?	?
economic news dependency	>50%	yes	yes	yes	yes
low efficiency	>>50%	yes	no	yes	yes
better estimation of news	>50%	yes	yes	yes	yes
volatility dependency	>50%	no	yes	yes	yes
market price manipulations	>50%	no	yes	yes	yes
insider trading	>50%	yes	yes	yes	yes
high efficiency	>>50%	no	no	yes	no
random walk primary steps	50%	no	no	no	no

financial profit making. The purpose of this research is also to simplify the difficulties for the practitioners due to the complicated theoretical background of this financial market topic. In the research we have resolved (chapter 4) the market price step development to the certain sequence (direction probability determination → time delay → price step creation finish) and we have discussed the role of each part of the sequence in the market situations which we have analyzed. We have also quantified forecasting advantage to assess our possible success. In the research we have recognized that not all the situations which are allowing the better forecasting may be simply used also for the profit making. For the conclusions on the profit realizing opportunities we have defined the hidden rule inside the market. We have concluded that if the rule is commonly known the possibility to use the rule for a profit making is then decreasing. All the general requirements on the profitable market situations according to this research are summarized in the chapter 5. We have also stated that the opportunity of making the repetitions of particular investments could be the certain advantage within the meaning of the chapter 2 and the law of large numbers. From this reason we have solved the directional dependence mainly on the short-term (daily) basis and according to this for example the long-term buy-hold strategy is connected to the more uncertain final result.

Instead of the long-term dependencies which are generally considered to be present within financial markets we can conclude that the short-term dependencies have been also confirmed and they are probably responsible for the empirically measured shape of financial market distributions (Dynamic Financial Market Model). The question about their practical value is still opened. According to the results from the simulations (Stádník 2011) and also from the empirical measurements (Stádník 2012) the forecasting advantage is not significantly above 1% in the case of for example the price inertia feedback. Forecasting advantage of 1% is due to its low value useful only in the case of high number of repeated investments and with transaction costs lower than 1%. Other possibilities may be offered by usage of technical analysis or other tools and feedback processes.

The other opportunities applicable for the better forecasting are described in the chapter 8 and their summary according to this research (within the meaning of chapter 5) is in the table 1. In the table 1 there is also analyzed the case of an independent symmetric random walk for the comparison. Determined value of the probability of the next price step direction is expected to be higher than 50 % in all the considered situations instead of an independent symmetric random walk. The time delay between the moment of the probability determination and the time when the step is done may be considered in the situations connected to economic news (instead of high efficiency case). The hidden rule can be found in all the situations except the low and high efficiency cases and of course in the case of an independent random walk steps. "Question mark" in the table means that in the situation of primary steps dependency the forecasting advantage is very close to 1% which probably does not cover the transaction costs.

In this study we have also provided the detailed discussion on validity of the directional dependence models on one hand and the models with the volatility dependence on the other hand. As we are able to explain financial markets effects using the both, the decision between the models about correctness should arise from the question: "Which model has the better economic explanation?" Based on the Monte Carlo simulations that we have done in this research we have concluded that the volatility dependence models are able to simulate observed departures from normality but they have the difficulties on economic interpretation. The economic interpretation of the models which use the directional dependence is much easier. Discussed volatility dependency can be eventually used for better market price forecasting of investment instruments which price depends on the volatility (for example financial options).

The research has been supported by the institutional grant VŠE IP 100040.

References

Anatolyev, S.; Gerko, A. 2005. A trading approach to testing for predictability, *Journal of Business and Economic Statistics* 23: 455–461. http://dx.doi.org/10.1198/073500104000000640

Baum, L. E.; Petrie, T. 1966. Statistical Inference for Probabilistic Functions of Finite State Markov Chains, *The Annals of Mathematical Statistics* 37(6): 1554–1563. http://dx.doi.org/10.1214/aoms/1177699147

Birchenhall, C. R.; Osborn, D. R.; Sensier, M. 2001, Predicting UK Business Cycle Regimes, *Scottish Journal of Political Economy* 48(2): 179–195. http://dx.doi.org/10.1111/1467-9485.00193

Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics* 31: 307–327. http://dx.doi.org/10.1016/0304-4076(86)90063-1

Buckley, I.; Saunders, D.; Seco, L. 2008. Portfolio Optimization When Asset Returns Have the Gaussian mixture distribution, *European Journal of Operational Research* 185(3): 1434–1461. http://dx.doi.org/10.1016/j.ejor.2005.03.080

Campbell, J. Y.; Hentschel, L.1992. No news is good news: An asymmetric model of changing volatility in stock returns, *Journal of Financial Economics* 31: 281–318. http://dx.doi.org/10.1016/0304-405X(92)90037-X

Chang, B. Y.; Christoffersen, P.; Jacobs, K. 2010. *Market Volatility, Skewness, and Kurtosis Risks and the Cross-Section of Stock Returns.* Working Paper, McGill University.

Cont, R. 2005. *Volatility Clustering in Financial Markets: Empirical Facts and Agent–Based Models.* Working Paper, Centre de Math´ematiques appliqu´ees, Ecole Polytechnique F-91128 Palaiseau, France.

Diebold, F. X.; Lopez, J. 1995. Modeling Volatility Dynamics, in K. Hoover (Ed.). *Macroeconometrics: Developments, Tensions and Prospects.*Boston: Kluwer Academic Press, 427–472.

Dzikevičius, A.; Vetrov, J. 2012. Stock market analysis through business cycle approach, *Business: Theory and Practice* [Verslas: teorija ir praktika] 13(1): 36–42.

Engle, R. F. 1990. Discussion: Stock Market Volatility and the Crash of 87, *Review of Financial Studies* 3: 103–106. http://dx.doi.org/10.1093/rfs/3.1.103

Engle, R. F. 1995. *ARCH: Selected Readings.* Oxford, UK, Oxford University Press.

Fama, E. 1966. The Behavior of Stock-Market Prices, *The Journal of Business* 38(1): 34–105. http://dx.doi.org/10.1086/294743

Henriksson, R. D.; Merton, R. C. 1981. On the Market Timing and Investment Performance of Managed Portfolios II – Statistical Procedures for Evaluating Forecasting Skills, *Journal of Business:* 513–533. http://dx.doi.org/10.1086/296144

Hsieh, D. A. 1991. Chaos and Nonlinear Dynamics: Application to Financial Markets, *Journal of Finance* 46: 1839–1877. http://dx.doi.org/10.1111/j.1540-6261.1991.tb04646.x

Huang, J.; Wang, J. 2010. *Liquidity and Market Crashes,* Review of Financial Studies.

Jondeau, E.; Rockinger, M. 2003. Conditional Volatility, Skewness, and Kurtosis: Existence Persistence, and Comovements, *Journal of Economic Dynamic and Control*: 1699-1737.

Krolzig, H. M. 1997. International Business Cycles: Regime Shifts in the Stochastic Process of Economic Growth. *Applied Economics Discussion Paper 194*, University of Oxford.

Larrain, M. 1991. Testing Chaos and Nonlinearities in T-bills Rates, *Financial Analysts Journal* September-October: 51–62. http://dx.doi.org/10.2469/faj.v47.n5.51

Lillo, F.; Farmer, J. D. 2004. The Long Memory of the Efficient Market, *Studies in Nonlinear Dynamics & Econometrics*: 8–13.

Lo, A. W.; Mamaysky, H.; Wang, J. 2000. Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation, *The Journal of Finance* 55(4): 1705–1770. http://dx.doi.org/10.1111/0022-1082.00265

Lux, T.; Marchesi, M. 2000. Volatility clustering in financial markets: a micro simulation of interacting agents, *International Journal of Theoretical and Applied Finance* 3: 675–702. http://dx.doi.org/10.1142/S0219024900000826

Markowitz, H. M. 1952. Portfolio selection, *Journal of Finance* 7(1): 77–91.

Masteika, S.; Rutkauskas, A.V. 2012. Research on futures trend trading strategy based on short term chart pattern, *Journal of Business Economics and Management* 13(5): 915–930. http://dx.doi.org/10.3846/16111699.2012.705252

Peiro, A. 1999. Skewness in financial returns, *Journal of Banking & Finance* 23: 847–862. http://dx.doi.org/10.1016/S0378-4266(98)00119-8

Pesaran, M. H.; Timmermann, A. 1995. Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50: 1201–1228. http://dx.doi.org/10.1111/j.1540-6261.1995.tb04055.x

Peters, E. 1989. Fractal Structure in the Capital Markets, *Financial Analysts Journal* July-August: 32–37. http://dx.doi.org/10.2469/faj.v45.n4.32

Peters, E. 1991. *Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility.* John Wiley & Sons, New York.

Peters, E. 1994. *Fractal Market Analysis: Applying Chaos Theory to Investment and Economics.* John Wiley & Sons, New York.

Rutkauskas, A. V.; Miečinskienė, A.; Stasytytė, V. 2008. Investment Decisions Modelling along Sustainable Development Concept on Financial Markets, *Technological and Economic Development of Economy* 14(3): 417–427. http://dx.doi.org/10.3846/1392-8619.2008.14.417-427

Rydberg, T. H.; Shephard, N. 1999. Modeling Trade-by-trade Price Movements of Multiple Assets Using Multivariate Compound Poisson processes. *Working Paper Series 1999-W23*, Nuffield College, Oxford.

Schiller. 2003. *From Efficient Market Theory to Behavioral Finance.* Yale University.

Sharpe, W. F. 1963. A simplified model for portfolio analysis, *Management Science* 9(2): 277–293. http://dx.doi.org/10.1287/mnsc.9.2.277

Stádník, B. 2011. *Dynamic Financial Market Model and Its Consequences.* Available at SSRN: http://ssrn.com/abstract=2062511.

Stádník, B. 2011. Explanation of S&P500 Index Distribution Deviation from a Gaussian Curve (Dynamic Financial Market

Model), *Journal of Accounting and Finance* 11(2): 69-77. USA, North American Business Press. ISSN 2158-3625.

Stádník, B. 2012. Testing of Market Price Direction Dependence on US Stock Market, *Business, Management and Education* 10(2): 205–219. SSN 2029-7491 print / ISSN 2029-6169 online.

Stankevičienė, J.; Gembickaja, N. 2012. Market Behavior: Case Studies of NASDAQ OMX Baltic, *Business, Management and Education* 10(1): 110–127. ISSN 2029-7491 print / ISSN 2029-6169 online.

Štěcha, J.; Havlena, V. 1993. *Teorie dynamických systémů* [Dynamical Systems Theory]. Praha.

Trešl, J.; Blatná, D. 2007. Dynamic Analysis of Selected European Stock Markets, *Prague Economic Papers* (4): 291–302. Praha.

Vacha, L.; Barunik, J.; Vosvrda, M. 2009. Sentiment Patterns in the Heterogeneous Agent Model, *Prague Economic Papers* (3): 209–219. Praha.

Wei, H.;Yoshiteru, N.; Shou-Yang. 2005. Forecasting stock market movement direction with support vector machine, *Computers & Operations Research* 32: 2513–2522 W. http://dx.doi.org/10.1016/j.cor.2004.03.016

Witzany, J. 2013. Estimating Correlated Jumps and Stochastic Volatilities, to appear in *Prague Economic Papers* 3.

Bohumil STÁDNÍK. Ph.D. Senior lecturer at University of Economics in Prague, Czech Republic. Research interests: financial engineering, modeling of financial market dynamical processes, market price development and forecasting, theory and practice of fixed income securities.