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Spring oscillations within financial markets

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Abstract

In this financial engineering study we suggest a new realistic economic explanation of the price volatility clustering within worldwide financial markets. The suggested clustering mechanism is based on the cooperation of feedbacks which we empirically observe and which are also connected to a momentum and level trading techniques. The explanation could be considered as an additional one to the current volatility clustering theories and its usage is mainly for short time volatility series. The research is the basic one in the area of the market price development.

Keywords: Price oscillations; volatility clustering; directional dependence; feedbacks; damped oscillations.

1. Introduction

The main contribution of this financial engineering study is to suggest a new realistic economic explanation (termed as "spring oscillation effect") of the price volatility clustering which we empirically observe within the worldwide financial markets. Using such explanation we are able to explain the volatility clusters without effects like economic news clustering or switching of the market between periods of high and low activity. The explanation is an additional one to the current theories of volatility clustering. The aim of this research is not to find particular parameters of the clustering mechanism but to propose functional general mechanism with the realistic financial interpretation and outline functional scientific framework for future studies in this area.

The volatility clustering is commonly connected to the price volatility dependence but in this research we use certain directional dependence mechanisms which are able to create volatility clusters and which are comprehensively described in the Dynamic Financial Market Model (Stádník, 2011a; 2011b). The model puts

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emphasis on realistic financial explanation and it is based on the direction dependence caused by feedbacks which are also responsible for the departures from normality in the price distributions. The idea of feedbacks is based on empirical observations where 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. Feedback is triggered or cancelled according to the past or current circumstances. Feedback can work together or against another feedback. According to the Dynamic Financial Market Model presumptions we expect more financial mechanisms which use feedbacks and which are involved in the following groups: price development limits, technical analysis, trend stabilizer, price inertia, trading techniques, different up/down movements, market price manipulations, market regulations, round numbers, logarithmic correction of a price, etc. However complex modelling of financial markets in this way is not so frequent. Some studies of directional dependence are based on the presumption that economic patterns may recur in the future. Also commonly used technical trading rules are based on the market price directional forecasting according to the past. We meet many other interesting detailed works or case studies in the area of the development direction dependence (Henriksson & Merton, 1981; Anatolyev & Gerko, 2005, study about the connection of liquidity and market crashes done by Huang & Wang, 2010; other works like Vacha, Barunik, & Vosvrda, 2009; Primbs & Rathinam, 2009; Lux, 2011). Price direction development dependence also takes place in the basic feedback process according to the 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 other works like short term trend trading strategy in futures market based on chart pattern recognition (Masteika & Rutkauskas, 2012) or development of the conception of sustainable return investment decision strategy in capital and money markets (Rutkauskas, Miečinskiene, & Stasytyte, 2008). We also have to mention work of Larrain, 1991, which state that long term memory exists inside the financial market and other similar work of Hsieh, 1991; Peters, 1989 and 1991 which focus mainly on measurement of probability diversions from normality. All the mentioned studies supporting a suspicion that a certain form of the directional dependence may cause also effects like sequence of damped oscillations which has a similar form to the observed volatility clustering.

On the other hand a wide range of models currently uses the volatility dependency. For example Buckley, 2008 has used in his work the Gaussian mixture distribution. Gaussian mixture has an acceptable interpretation: financial market performs in two regimes with high and low volatility. Gaussian mixture is able to model departures in the distribution and also volatility clusters 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 the Markov switching model (Krolzig, 1997; etc.) Other famous works in this area were done by Bollerslev, 1986, GARCH process; Engle, 1995, ARCH process. Some new research in the area of volatility dependence was done by Witzany, 2013 ("Estimating Correlated Jumps and Stochastic Volatilities") or Roch, 2011. While GARCH, ARCH and other stochastic volatility models propose statistical constructions based on volatility clustering in financial time series, they do not provide any economic explanation.

The realistic economic explanation of volatility clustering using standard theories is difficult. The simplest idea is that volatility clustering is caused by switching of the market between periods of high and low activity or clustering of economic news. These effects are typical volatility dependency cases but they are not able to explain volatility clustering inside the time periods without economic news arrival or in very short periods. We also have other explanations like the competition between more trading strategies but the simulation does not allow confirming mechanism being responsible for volatility clustering (Cont, 2005). Volatility clustering could also arise from switching of market participants between fundamentalist and chartist behavior (Lux & Marchesi, 2000). According to Cont, 2005, the origin of volatility clustering can be also caused by threshold response of investors to news arrivals. Volatility clustering also could be connected to a clustering of trading activity (Chordia, Roll, & Subrahmanyam, 2001) due to switching between two periods of higher and lower economic uncertainty.

2. Spring oscillation effect description and simulation

Volatility clustering within financial markets can be, according to the first point of view, visually compared to the sequence of repeated damped oscillations of a mechanical spring (Figs 6, 7, 8) which are randomly hit by external disturbances. If we find really existing “forces” within the financial market which are analogical to the forces which are responsible for the mechanical oscillations we can apply appropriate description from physics to finance. To make such identification is the core of this research. In the case of damped mechanical oscillations we work with the mass inertia, we work with the force, which acts against the movement, and its value is perpendicular to the deviation from the equilibrium position and finally with the damping caused by a mechanical friction. The oscillation is triggered by an external impulse.

General mechanical force can be in finance represented by mentioned feedbacks increasing the value of probability of next price step up or down direction (from 50/50% for the pure random walk to for example 51/49) thus causing certain movement dynamics with acceleration and consequently a certain speed of the price change.

Mass inertia can be in finance represented by a momentum of a price movement, which keeps the movement in a certain direction and which is also described in the Dynamic Financial Model as the trend stabilizer feedback. For example momentum trading when traders try to find instruments that are moving significantly in one direction on high volume and try to participate in the profit from this movement is based on this mechanism. Momentum traders may hold their positions for a few minutes, hours or even the entire length of the trading day. Traders are supporting the trend by their own orders and therefore we speak about the feedback to the past influencing the future development direction. The research in the area of momentum trading has been done by Pesaran & Timmermann, 1995; Chan, Jegadeesh, & Lakonishok, 1996; Stankevičienė & Gembickaja, 2012; Donefer, 2010; Easley, Prado, & O'Hara, 2011, 2012; Fabozzi, Focardi, & Jonas, 2011; Franck, Walter, & Witt, 2013; Rey & Schmid, 2007.

Mechanical force which is pushing the mass against the movement and which is proportional to the distance from the equilibrium can be financially interpreted as the price inertia feedback which is pushing the market price back to a certain level and which is also described in the model. The certain level can be for example the price level which was set after the last economic news of high importance. The value of the force is increasing with the market price deviation from the level as the activity of traders attempting to participate on the price turnover (level trading) is also increasing in this case.

Mechanical damping in finance can be represented by gradual satisfying of orders which have triggered the oscillation; thus we expect the damping to be proportional to the change of price per a time unit; or by the decreasing of market activity or by changing of the market situation due to other market circumstances.

The price oscillations are usually triggered by buy or sell order or by economic news.

The equation 1 is the general equation describing damped oscillation movements. It is the second-order homogeneous differential linear equation. If we apply the equation on the price movements then the left side of the equation represents the acceleration of the price change where y is the deflection from the initial value (the value before the oscillations triggering) at time t and constant c_1 is connected to the trend stabilizer; constant c_2 is connected to the damping and c_3 belongs the price inertia feedback. In this case we expect the pure cooperation of momentum and price inertia feedbacks without any random component.

$$c_1 \frac{d^2 y}{dt^2} = -c_3 y - c_2 \frac{dy}{dt} \tag{1}$$

The particular solution has a specific form:

$$y = Ce^{\alpha t} \tag{2}$$

and α_1, α_2 can be expressed from the characteristic equation:

$$c_1\alpha^2 + c_2\alpha + c_3 = 0 \tag{3}$$

α_1, α_2 equals:

$$\alpha_{1,2} = \frac{-c_2 \pm \sqrt{c_2^2 - 4c_1c_3}}{2c_1} \tag{4}$$

Under the condition:

$$4c_1c_3 < c_2^2 \tag{5}$$

we consider over-damping without oscillation (Fig. 1a). The dominant force is the price inertia feedback and the price returns to the initial value in the fastest way. The result is a linear combination of two particular solutions:

$$y(t) = C_1 e^{\alpha_1 t} + C_2 e^{\alpha_2 t} \tag{6}$$

Under the condition:

$$4c_1c_3 = c_2^2 \tag{7}$$

we observe critical damping (Fig. 1b) when the price returns to the initial value also without oscillation. The dominant force is the price inertia feedback. The solution has form:

$$y(t) = (C_1 + C_2 t) \cdot e^{-\frac{c_2}{2}t} \tag{8}$$

In these both cases we do not observe typical oscillations.

Under the condition:

$$4c_1c_3 > c_2^2 \tag{9}$$

α_1, α_2 are complex conjugates:

$$\alpha_{1,2} = \frac{-c_2 \pm i\sqrt{4c_1c_3 - c_2^2}}{2} \tag{10}$$

The cooperation of the price inertia feedback and the trend stabilizer causes typical damped oscillation. A possible forms of the oscillations depends on the constants c_1, c_2, c_3 (Fig. d in 1c, d, e, and f). The solution has form (equation 11):

$$y(t) = C\ e^{-\frac{c_2}{2}t} \sin(\frac{\sqrt{4c_1c_3 - c_2^2}}{2} t + \gamma) = C\ e^{-bt} \sin(\omega t + \gamma) \tag{11}$$

$$c_1 \frac{d^2 y}{dt^2} = -c_3 y + c_2 \frac{dy}{dt} + c_4 R(t, y) \tag{12}$$

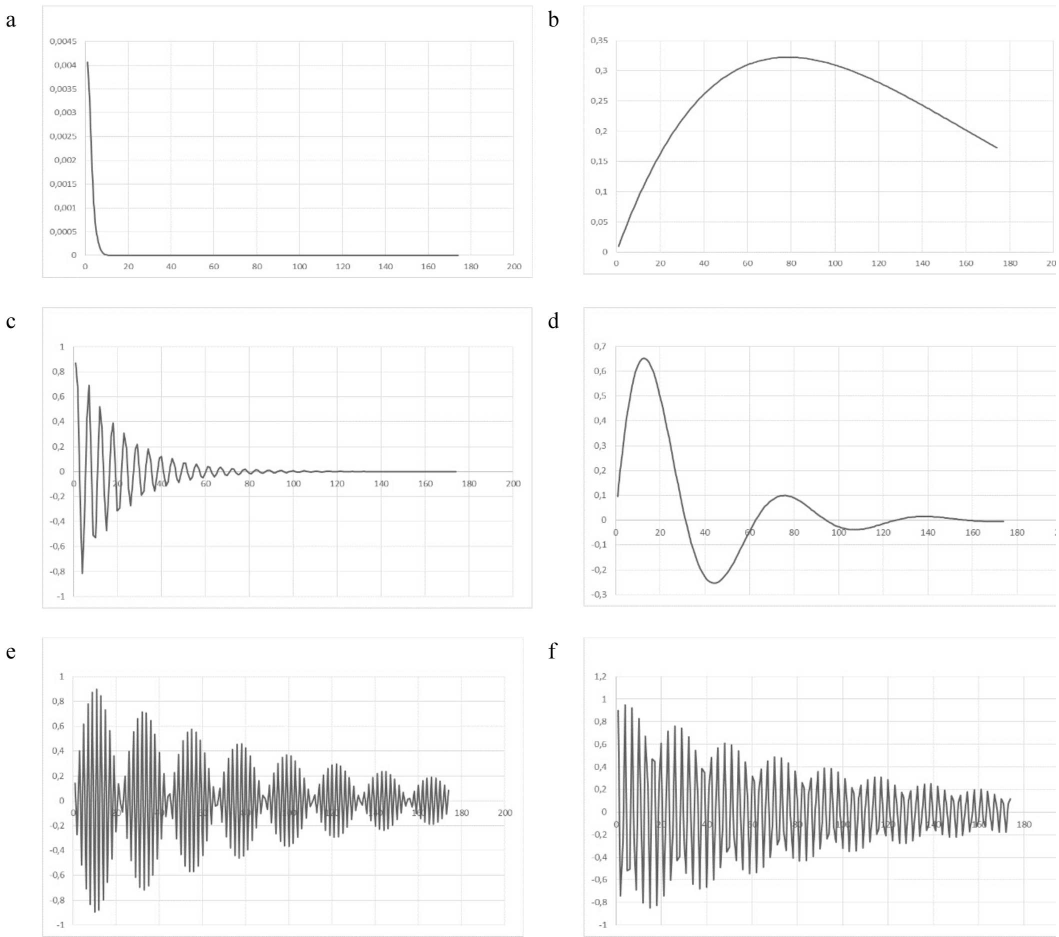

Fig. 1. Examples of under-damped oscillations (c, d, e, f), over-damping (a) and critical damping (b)

Denotations b and ω are taken from a common technical formalism, where b is the constant of damping and ω is an angular velocity of an oscillation motion.

Depending on the parameters b and ω we can model different style of the oscillations which are based on real market observed price fluctuations.

There are unrealistic situations in the Fig. 1 and to be more in accordance with reality we have to consider also some random component $R\ (t,y)$ inside the oscillation process (equation 12) which cause observed disturbances. Such a random component is basically random additional acceleration of a price change and for our simulations we expect its uniform distribution around the equilibrium position. The uniform distribution is economically supported by, for example, the external factors (incoming economic news) or internal factors (traders who use different techniques than momentum or price inertia trading) and these factors do not depend on the state of an oscillation. The simulation of the random component in the oscillations in the Fig. 2a is in the Fig. 2b which is then more in accordance with a realistic development.

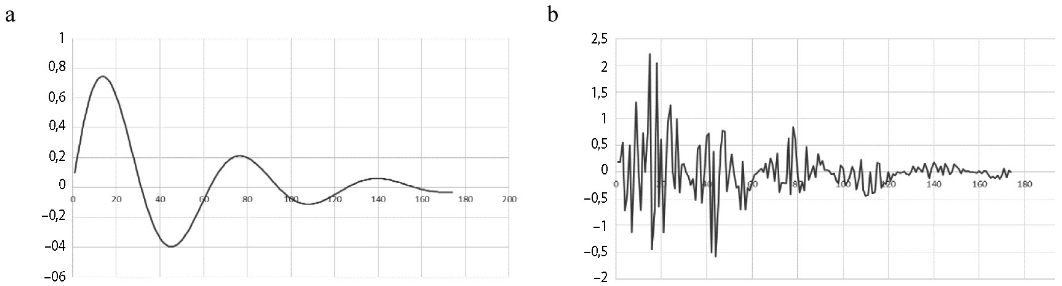

Fig. 2. Simulation of damped oscillations (a) with the random process (b)

The results of complex simulation at time of a market volatility development based on the spring effect with the random disturbances are in the Fig. 3a, b. The initial impulse which triggers the spring effect also occurs at random time (uniform distribution) in the simulation. Autocorrelation of volatility data series in the simulation according to Fig. 3a is 0.211. Similar simulation in the Fig. 3b (autocorrelation of volatility data series: 0.124) uses two regimes of a trend stabilizer and price inertia forces (higher and lower) and also triggering of the oscillation at random time. The value of autocorrelation is in good accordance with the realistic volatility series in the Figs 4, 5, 6.

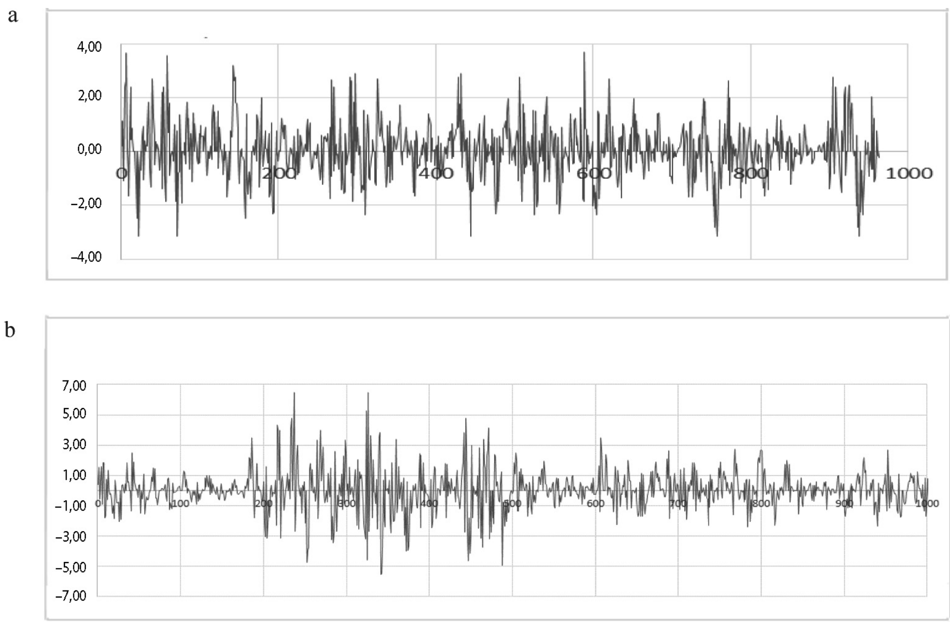

Fig. 3. Simulation of clustering based on damped oscillations (a), (b)

The spring effect which is based on the directional dependence provokes the question of possible price directional forecasting. We expect nowadays this rule is partly hidden but even in the case of its usage the predictability advantage is probably not to much higher than 1% which does not cover the transaction costs (Stádník, 2012, 2013a).

3. Spring effect empirical observations

In the 1 min. volatility data series (Fig. 4a, b) we observe volatility clusters on Euro-Bund contract. These volatility clusters can be very well explained by the price inertia and the trend stabilizer spring effect. The existence of these effects is economically supported by the coexistence of high frequency momentum trading and also by the high frequency price inertia (level) trading.

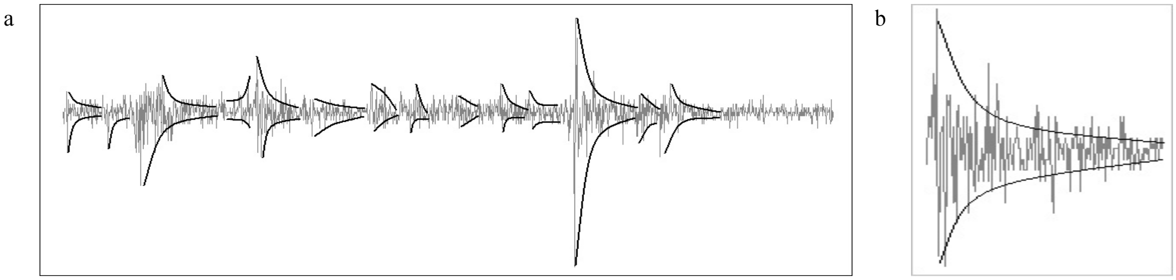

Fig. 4. Example of damped oscillations sequence in **1** minute volatility series with damped oscillations of Euro-Bund Futures (FGBL, EUREX) (a), detailed (b)

In 10 minutes volatility data series (Figs 5a, b) we also observe volatility clusters but with a slightly different shape that in 1 minute time period (Fig. 5a, b).

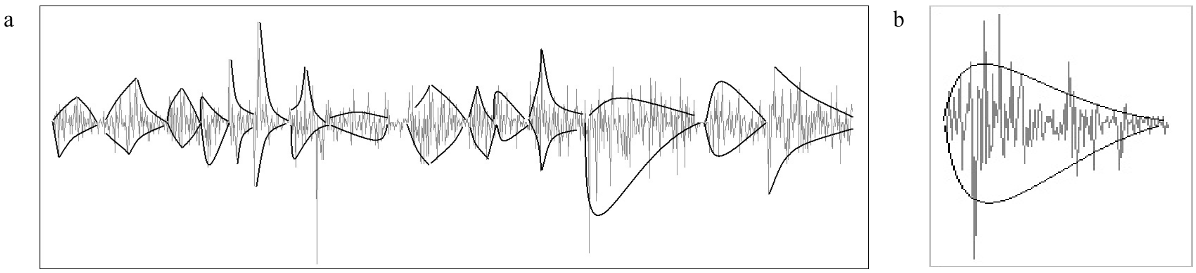

Fig. 5. Example of damped oscillations sequence in 10 minutes volatility series of Euro-Bund Futures (FGBL, EUREX) (a), detailed (b)

In the Figs 6a, b there are volatility clusters in EUR/USD 5 minutes which can also be very well explained using the spring oscillation effect.

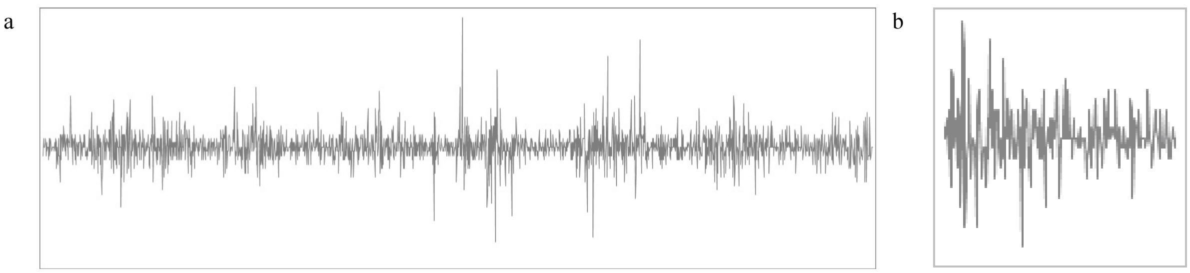

Fig. 6. Example of damped oscillations sequence in 5 minutes volatility series of EUR/USD (a), detailed (b)

4. Conclusions

The main contribution of this financial engineering research is the suggestion of a realistic economic explanation of the price volatility clustering which we empirically observe within the worldwide financial markets. The explanation is an additional one to the current theories of volatility clustering and it is useful especially in short time periods. We propose clustering mechanism – spring oscillations effect which is based on the cooperation of price inertia and trend stabilizer feedbacks. The mechanism is connected to a momentum trading which we have identified within the financial market. The effect works in the similar way as a mechanical oscillations depending on the parameters of the particular processes. Using such explanation we are able to explain the volatility clusters in the time periods where we don´t observe effects like economic news clustering or switching of the market between periods of high and low activity. In the research we outline the appropriate mathematical description and we also do provide simulations of the real financial market situations. The spring effect which is based on the directional dependence provokes the question of possible price directional forecasting.

The aim of this research is not to find all the particular parameters of the clustering mechanism but to propose a functional scientific framework with the realistic financial interpretation.

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