TOWARDS A HOLISTIC APPROACH FOR MODELING FINANCIAL VOLATILITY

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ABSTRACT

Due to the more global economic system, financial markets impact to society and family throughout the world and causing new global crisis because of the higher and faster volatility of financial prices. This paper proposes a system view to set the basis for modeling the dynamics of global financial market with a holistic system view, in order to achieve a global sustainable development.

Keywords: Economic system, financial markets, derivatives, volatility, holistic, systems.

INTRODUCTION

New global economic and capital system both are under stress because of the recent global financial crisis. Therefore, world economic, financial markets, banking system, manufacturing system, housing market, unemployment rate hikes, all faces great difficulties and challenges.

The economic system is composed by production and service systems. Production system takes high capital intensive investment, requiring time and inventory to complete sells; service system (such as financial institutions: banking and insurance companies) is not capital intensive, due to it produces profit through complete selling contracts. Specifically, financial service and products, offered in financial markets, is low capital investment and high selling skill with no inventory and can create big market if they can convince customers that they are working for them and helping them make money for their money. However, the volatility of the world financial markets (such the stock market) it does making a great impact to the wealth and buying power of general public.

Manufacturing industries makes products which meet our daily needs and/or wishes. It takes time, material, labor, equipment, and technology to accomplish the task and under a great competition which could drop out the business. On the other hand, financial service industries make money by trading financial products (such as stocks, options, futures, insurance contracts, and securities) in financial markets. With very financial volatility, wealth and buying power can change overnight or in a very short period time either gaining or bankrupt. Psychological behavior plays a very important part of a decision and its outcome especially in financial markets. Therefore, it is necessary to face the new global financial crisis and understand global future sustainable development from a more holistic view to the future because it mixes hard (e.g. stochastic volatility models) and soft (e.g. the viable system model) approaches for tackling problems of real-world systems.

THE GLOBAL FINANCIAL AND ECONOMIC CRISIS

A general economic system includes many factors: goods and/or services, input costs, profit or loss, international trade (import and export), industrial productivity, output quantities, pricing level, employment rate, households' disposable income, capital expenditure and financial market, wealth, expectation, consumption pattern, etc. In this system, corporate sectors and public sectors are linked by financial markets to make fund flow from public to business.

We could search into detail factors which embedded in global economic system, such as natural resources consumption in the production process, and global competition and effect of global financial markets index role to demand, supply, and production and consumption impact. On the other side, financial products and global investment industries and fund managers impact to financial market instabilities and volatility. Technological, computer capability, and communication have made the world information and financial exchange in the spilt of second and value of a stock or money market fund could change billions of dollars in a matter of few second or couple of days throughout the world financial industries, it could cause tremendously disturbance to the global economic system. From a holistic view, it can be said that we have many critical issues unsolved in today's world. There are several major dimensions found imbalance such as technology, ecology and wealth (see Figure 1).

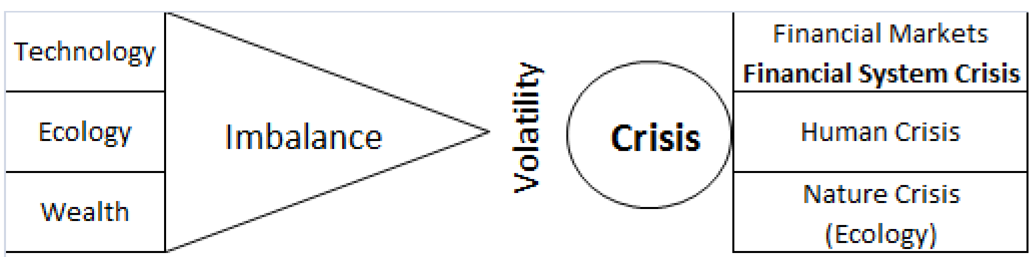

Figure 1. The relationship between imbalance-volatility and crisis.

A financial market is a place where buyers and sellers are ready to exchange various types of financial products. Financial markets are commonly divided into: (a) capital markets (stock markets and bond markets), (b) money markets, (c) derivative markets, (d) futures markets, (e) insurance markets, and (f) foreign exchange markets.

Over last decade, financial institutions, operating under a competitive free market environment, have been under immense pressure to earn more profits. Thus, they have resorted to more and more financial instruments like *derivatives* and developed an appetite for risk taking, often with money entrusted to them for safe custody by their clients. However, abuse of derivatives, as well as huge current account deficits of the US, deregulation, loose monetary policy, excessive liquidity, shoddy underwriting, negligence of credit-rating agencies and lax government oversight, contributed to origin and propagate the current global financial crisis.

While derivatives (e.g. futures, forward, swaps, options and warrants) are useful financial instruments for handling of financial risks due to volatility (Chance, 1997), abuse of these has a toxic effect when financial institutions assume risks that their volatility models cannot anticipate on time.

Derivatives were originally used to hedge commodities products such as agricultural products and metals from the Antique Greece. But the real birth of financial markets can be said to have come really in the 1970s because the system of fixed exchange rates went burst, President Richard Nixon had decided to abolish the Bretton Woods agreement, and the organized markets had decided to standardize their products. Derivative markets extended from the United States to Europe and Asia in the 1980s. In the last ten years, the derivatives business had become increasingly important in financial markets, being the total notional value of derivatives around 400 trillion dollars for the year of 2004 according to the Office of Controller of the Currency, while the Gross Domestic Product of the Unites States had only been around 10 trillion dollars in 2004. However, the fact that this market had been growing very rapidly precluded for a bubble burst, hence a greater irresponsibility from regulators and controllers to control and preserve the financial system. The bubble burst two years ago in the following terms: credit crunch, banking crisis, and the worst that has happened since the Great Depression. Expectedly, the financial industry is the worst affected, with bankruptcy, absorption, and the rest suffering sharp drops in financial prices (Heng and Tai, 2010).

The United States of America has been hit by the collapses or near-collapses of Bear Stearns, Indy Mac, Lehman Brothers, Washington Mutual, Wachovia, Fannie Mae, Freddie Mac, the American Insurance Group and the Citigroup. For example, with the Citigroup bailout added in, the current total cost exceeds $4.62 trillion, which is the biggest injection of funds in American history. There is general consensus that the world is facing the worst economic meltdown since the Great Depression.

Financial crises bear certain similarities with earthquakes. Long periods of calm are interrupted by short periods of violent tremors. During the calm period, pressure is slowly building up. A point is reached when disaster strikes. The tremors release the stress built up and after a while, calm returns. This cycle then repeats.

During the calm period the financial volatility is low, the system is stable, and the profit outlook is good. Under the pressure to reward investors with more profits, corporations take on more risk. They assume more debts in order to increase their productive capacity. Banks are just too keen to lend money to others. As stock prices climb, investors, having exhausted their funds, start to borrow to buy more stocks. Both corporations and investors take on more leveraging. This is a time of irrational exuberance when the bubble is building up.

When the bubble bursts, assets must be liquidated quickly to pay back the loan; money must be found to unwind the leveraging. In panic, investors rush for the door. Before long, we have a fire sale going on. Banks which cannot get their money back just going bankrupt, so they are very reluctant to lend to even viable businesses. We have a credit crunch, which aggravates the situation. To make the best out of the situation, management retrenches staff, persuades the rest to work harder without overtime pay, squeezes the suppliers and offers discounts to the buyers. If all these fail, the company goes bankrupt. Gloom overtakes euphoria and the economy slips into recession. The financial system reveals its fragility. Millions of innocent people become the victims of greedy speculators. A global financial crisis suggests the possibility of some fundamental weakness of the international financial system, and sparks calls for redesigning the international financial architecture. But when the hurricane blows over, it carries away with it the honest anxiety. It is business again as usual, until the next turmoil.

Undoubtedly, derivative markets have enabled us to have more tailor made transactions for hedger and risk speculators. Therefore, volatility has become the most important variable in the pricing of derivative securities, whose trading volume has quadrupled in recent years.

Financial market volatility can have a wide repercussion on the economy as a whole. For this reason, policy makers often rely on market estimates volatility as a barometer for the vulnerability of financial markets and the economy.

MODELING FINANCIAL VOLATILITY

Financial volatility is a key variable in the modeling of financial markets. It controls all the risk measures associated with the dynamics of price of a financial asset and also it affects the rational price of derivative products.

The volatility σ of a financial asset is a statistical quantity which needs to be determined starting from market information. It is the standard deviation of asset return (or of logarithm price changes of the asset). Different methodologies are used to infer volatility estimation from market data ranging from a direct calculation from past return data (historical volatility) to the computation of the volatility implied in the determination of an option price computed using the Black and Scholes formula or some variant of it. There is a large empirical evidence that volatility is itself a stochastic. Therefore, in this section, are presented some stochastic volatility models proposed in the financial literature by investigating their ability in modeling statistical properties detected in empirical data. These models have been developed under a Hard System Thinking, specifically under the framework of Operations Research process.

The three most important features of price volatility in financial markets are: low autocorrelations, non-normal distributions, and non-linear generating process (Taylor, 2005). So that, it is necessary to develop price volatility models which do not assume that returns have independent and identical distributions.

The simplest interesting model for volatility supposes that it follows a two-state Markov chain, but more volatility states are required to provide a realistic description of market prices. There are other two volatility models: the lognormal (autoregressive) model for a latent volatility variable (Taylor, 1982) and the ARMACH model (Bollerslev, 1986). The lognormal model is often called the stochastic volatility (SV) model and it defines the return r_t as its expectation μ plus the product of the volatility σ_t and an i.i.d. standard normal variable u_t,

$$r_t = \mu + \sigma_t u_t \qquad (1)$$

With

$$\log(\sigma_t) = \alpha + \phi(log(\sigma_{t-1}) - \alpha) + \eta_t \qquad (2)$$

Because these models has two random components (u_t and η_t) per unit time, it is impossible to exactly observe the realizations of the volatility process and difficult to estimate the parameters of the autoregressive AR(1) process for $log(\sigma_t)$. Several extensions of the above SV models have been investigated, e.g. replacing the normal assumption for the variables u_t by a Student-t distribution (Harvey, Ruiz and Shephard, 1994), introducing some dependence between u_t and either η_t or η_{t+1} (Yu, 2005), and replacing the AR(1) specification for the logarithm of volatility by a long-memory process (Breidt, Crato and de Lima, 1998).

The second volatility model, or the GARCH (1,1) model, defines the return r_t as its expectation plus the product of the conditional standard deviation $\sqrt{h_t}$ and an i.i.d. standard normal variable z_t,

$$r_t = \mu + \sqrt{h_t z_t} \qquad (3)$$

with

$$h_t = \omega + \alpha(r_{t-1} - \mu)^2 + \beta h_{t-1} \qquad (4)$$

The great advantage of this model, compared with SV models, is that there is only one random component (z_t) per unit time and hence, the likelihood function is easy to calculate as the product of conditional densities. The availability of maximum likelihood estimates explains why ARCH models are more popular than SV models in the research literature.

The general GARCH(p,q) model of Engle and Bollerslev (1986) and Bollerslev (1987) makes h_t a linear function of the p previous squared excess returns, and permitted the z_t to have a fat-tailed distribution. Glosten, Jagannathan and Runkle (1993) proposed the following extension of GARCH(1,1) defined by:

$$h_t = \omega + (\alpha_1 + S_{t-1}\alpha_2)(r_{t-1} - \mu)^2 + \beta h_{t-1} \qquad (5)$$

with $S_{t-1} - 1$ if $r_{t-1} < \mu$ and otherwise $S_{t-1} = 0$.

Other ARCH variations include working with linear functions or absolute values rather than squares (Schwert, 1989), making the conditional mean a function of h_t (Engle, Lilien and Robins, 1987), and specifying a long-memory process for h_t (Baillie, Bollerslev and Mikkelsen, 1996).

Inferences about volatility forecasting models are obtained directly by comparing methods for forecasting absolute returns. It is recommended that exponentially weighted moving averages of absolute returns are used to measure volatility, as they are robust against changes in the long-run level of volatility and are also empirically as accurate as alternative methods. Volatility forecasts are of particular interest to risk managers and option traders (e.g. Poon and Granger, 2003). The best forecasting methods rely upon volatility levels implied by option prices and upon high-frequency returns, typically by using measures such as daily sum of squared five-minute returns (e.g. Blair, Poon and Taylor, 2001).

Methods for valuing options, when the volatility is stochastic only provide valuations that are approximately correct. The general theory for pricing options in a stochastic volatility economy is presented by Hull and White (1987). Some special cases have closed-form valuation equations. In particular, the remarkable paper by Heston (1993) shows how to value options when the continuous-time process for volatility is a square-root process; his results are generalized by Duffie, Pan and Singlenton (2000) to also allow for jumps in the prices process.

The empirical analysis of high-frequency returns (from prices recorded every five minutes) have found that high-frequency returns display the same stylized facts as daily returns, but additionally they have also substantial variations in the average level of volatility during the day. Some of this variation can be explained by macroeconomic new announcements.

Volatility can be estimated, modeled and predicted more accurately by using high-frequency returns. Much recent research has focused on the information conveyed by realized volatility, which is defined as the square root of the sum of the squares of intraday returns. Realized volatility has been found to have an approximately lognormal distribution and a long-memory property (Andersen *et al.*, 2001a, 2001b). Furthermore, the distribution of daily returns conditional upon realized volatility is approximately the lognormal-normal distribution of Clark, one of the most interesting subjects of current research is the detection of jumps in the price process, using methods pioneered by Barndorff-Nielsen and Shephard (2006).

However, financial markets are very complex systems which can be analyzed and modeled using non-linear approaches such as the fractal analysis. The study of the complex systems in the frame work of fractal theory has been recognized as a new scientific discipline, being sustained by advances that have been made in diverse fields ranging from physic to economics. For instance, Morales, Tejeida and Badillo (2010) discussed the characterization of oil crude price volatility under a fractal framework, finding a transition from anti-persistent to persistent behavior of the volatility in the horizon scale was observed: this transition was accompanied by the change in the type of volatility distribution, which was light-tailed for short horizons and it was heavy-tailed for long horizons. In pragmatic terms, this means that oil crude price volatility displayed positive correlations, so it is possible to predict the oil crude price behavior for long horizons.

CONCLUSIONS

In this paper are presented some stochastic volatility models proposed in the financial literature by investigating their ability in modeling statistical properties detected in empirical data. These models have been developed under a Hard System Thinking, specifically under the framework of Operations Research process. Perhaps, the volatility models for forecasting the price dynamics have been improving their accuracy, but they cannot avoid yet, or at least mitigate, the effects of volatility in financial markets. Thus, it is necessary to develop and/or apply models that consider the system from a holistic view by

including the (social) relationships among the markets participants such as investors, brokers, traders, regulators, and structures.
As a starting point of a new dimension of thinking and modeling for finding new ways for global financial market and economic system, to revive business communities, government public policy for welfare of the general public and private citizen, we propose to take into account the following aspects:

1. To build the fundamental economic system from its parts to holistic system in order to see the dynamic economic system function and will be able to use simulation method (hard tools) to see how system behaves under different condition or inputs and can be used as monitor system for policy making and understanding the status, state, consequence to ongoing development.
2. Examine how its parts relate to the system performance and outcome, i.e. financial volatility. Mathematic models (such as stochastic volatility models) will be use to describe the system relationship among each parts. Statistical goodness of fit to capture subsystem behavior in the past and parameters impacts to system shocks. Understanding system parameter and model building could help achieved global sustainable development continue retrace back down how economic system behavior response to each state (e.g. Production side vs. Service side, Demand vs. Supply, etc.) at different state.
3. Understanding the dynamics of financial market as well as its role in economic system before it breaks down in new era where global is link closely together. Using Closed System from global market to see the entire financial product and financial volatility how they actually effect global monetary system.
4. Examine the monetary flow through the economic system; we can use the control theory or perturbation analysis to see the system outcome with respect to monetary flow quantity and required buffers through each parts and stations in the global financial economic system. International Monetary Fund serves as a global financial system well in the past, but, with recent globalization and innovated financial products and more global participants or individuals, it drastic changes the traditional patterns.
5. Environmental impact and global warming are also new issues that business needs to deal with how effectively they use the resource to produce the product.

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