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A re-examination of maturity effect of energy futures price from the perspective of stochastic volatility

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A B S T R A C T

This paper selects stochastic volatility (SV) as the uncertainty or volatility measure to re-examine the Samuelson hypothesis of maturity effect (SHME) (Samuelson, 1965). Stochastic dominance is used to examine whether the stochastic volatility level dominates with respect to maturity. The empirical analyses of energy-futures price series generally provide mild support for this hypothesis in terms of the first two degrees of stochastic dominance. Each type of futures has its own properties with respect to the maturity effect. SV levels play a role in determining the testing outcome. The hypothesis is more likely to hold at low SV levels. The higher the volatility level, the less likely the SHME will hold because SV surges to its peak level regardless of maturity.

1. Introduction

In his seminal works, Samuelson (1965, 1976) postulates that the volatility of a futures price increases as maturity decreases. Volatility is the conditional standard deviation of a return series of futures and a measure of its risk or uncertainty level. Kolb (1997) attributes this phenomenon to the increase in the pace at which information is acquired as the contracts near maturity. That is, the futures prices become more volatile as more relevant news is released as the delivery date nears. As maturity approaches, the futures price must converge to the spot price. The futures prices do not necessarily respond instantly and significantly to the arrival of new information. This leads to strong reactions by futures prices once new information is disseminated, especially right before the maturity date. This conclusion is called the Samuelson hypothesis of maturity effect (SHME).

This hypothesis underscores the crucial role that time-varying volatility plays in quantitative risk management, at least in the topics of futures trading (speculation and hedging), derivative pricing (e.g., futures and option on futures), risk measurement, futures market efficiency, and margin setting (Houthakker and Williamson, 1996; Focardi and Fabozzi, 2004). For example, generally in energy futures trading, the higher the futures price variability, the higher minimum margin requirement. Accordingly, the validity of SHME dictates whether we can reduce speculation and volatility by determining the minimum margin requirement of futures traders (Serletis, 1992a).

Previous literature provides mixed conclusions about the empirical examination of the SHME. For example, Serletis (1992a), Galloway and Kolb (1996), and Beaulieu (1998) provide strong supporting evidence for the SHME. Liu (2014), Gurrola and Herrerias (2011), and Daal et al. (2006) render mildly supportive outcomes. Rutledge (1976), Milonas (1986), Chen et al. (1999), and Brooks (2012) arrive at contrary conclusions. There are at least six major implications from this inconclusiveness.

First, Samuelson's (1965, 1976) assumptions do not necessarily hold true in practice. The assumed stationarity in first-order autoregressive futures price series, i.e., martingale or ergodic process, are not usually supported by actual data. The implicit assumption that the standardized sample variances are normally or log-normally distributed is only good for the theoretical framework setup. The SHME may not hold when the cash price is nonstationary. The actual cash price exhibits non-constant variance. The assumption that the futures price equals the expected value of the settlement price at a delivery date is not supported by empirical findings, as concluded by Anderson (1985). Consequentially, SHME is not necessarily tenable due to these arbitrary assumptions. Alternatively, the distribution of the sample variances of futures price changes should be considered unknown, and the observed pattern of futures return volatility does not exhibit a systematic increasing or decreasing trend.

Second, variance is not necessarily an appropriate measure for risk or uncertainty level (McNeil et al., 2005). Variance is defined as an

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aggregate measure of the symmetric deviation away from the mean. The variance estimate is contingent on the length of the data period. This measure cannot describe the volatility level on a point-by-point basis. Neither can this measure differentiate between positive and negative deviations from the mean. Further, variance can only be used for past-realized volatility. A rolling-window estimation of variance can help dynamically depict the volatility process, but the estimation outcomes are contingent on the arbitrary selection of window length. These inadequacies in the variance limit its empirical usefulness in the examination of the SHME. Alternatively, the unobservable contemporaneous volatilities are treated as latent (unobserved) random variables in a stochastic volatility (SV) framework. This framework has a noticeable advantage in that it can depict the volatility process in a point-wise manner and capture contemporaneous volatilities. This paper focuses on stochastic volatility as the level of volatility or uncertainty.

Third, as Samuelson (1976) highlights, the SHME is not suitable to short-term testing, thus the data period should be sufficiently long. However, this note is set aside in the previous empirical studies. Further, each futures price of a specific commodity has its own properties. There are several articles that claim to conduct "extensive," "vast," or "comprehensive" empirical exploration of futures contracts (Daal et al., 2006; Brooks, 2012). However, several articles have reached the same conclusions that SHME holds in agricultural markets but not in financial and metal markets (Bessembinder et al., 1996; Kalev and Duong, 2008; Duong and Kalev, 2008). Before judging the degrees of coverage of futures contracts, it is inappropriate to make an overall conclusion on numerous futures contracts based on the outcomes of tests of the SHME. In essence, the key issue in examining the SHME involves the data length more than the contract type, as Samuelson (1976) pointed out. To stress test the SHME, this paper selects an industry that contains one of the most volatile futures contracts: energy. The futures price series for empirical examination of the SHME in this paper are those for crude oil, reformulated regular gasoline, RBOB regular gasoline, No. 2 heating oil, and propane traded on the New York Mercantile Exchange (NYMEX). The U.S. Energy Information Administration has posted those data series, covering up to 29 years of daily data. This length of time from which data was used is generally longer than those in previous studies.

Fourth, confirmed time-varying volatility (heteroscedasticity) is endemic in financial markets. The previous empirical analyses rely mostly on time-series models (Engle, 1982; Engle and Bollerslev, 1986) to capture the conditional volatility process, e.g., Gupta and Rajib (2012). Tsay (2012) does provide some cautionary words, but they are generally overlooked. For example, unconditional density of financial return series show pronounced leptokurtosis. Time series of financial data show significant patterns of volatility as clustering and squared returns exhibit pronounced serial correlation. ARCH and GARCH models can be trapped into model misspecification. The conditional volatility is assumed stochastic, but those models specify that the time-varying volatility follows a parametric deterministic process. In addition, the performance of GARCH models in capturing the tail behavior remains limited even with standardized Student *t* innovation. Some significant properties presented in the time-series data could play a significant role in determining the outcomes of estimation and hypothesis testing; these include unit root, cointegration, causality, and structural break (Serletis, 1992b; Bekiros and Georgoutsos, 2008; Maslyuk and Smyth, 2009; Bekiros and Diks, 2008; Chen et al., 2014). The SV model is considered a better alternative in these regards. Anderson and Shephard (2009) echo this recommendations, stating that SV is superior in modeling leverage effect and considering excess skewness and kurtosis. Those advantages can help evaluate SHME at higher orders of moments. Further, Hafner and Preminger (2010) and Carnero et al. (2004) underline the significant flexibility of SV in capturing the empirical regularities due to its limited assumption and capacity in capturing contemporaneous volatilities.

Fifth, there are noteworthy constraints and challenges in SV estimation. By treating SV in a state-space formulation, one describes contemporaneous volatilities as latent random variables as opposed to the deterministic values. This formulation leads to the intractability of the likelihood function and prohibits its direct evaluation. This challenge is overcome by the introduction of Markov chain Monte Carlo (MCMC) for fully Bayesian implementation through the SV framework (Jacquier et al., 1994). This introduction has been further refined by Kastner and Frühwirth-Schnatter (2014) for a more efficient estimation. Thus, Bayesian parameter estimation via MCMC is adopted in this paper.

Sixth, in addition to the issues highlighted in the first point, such as unknown distribution of the sample variances of futures price, significant structural breaks are usually present in the SV series. These properties can have a considerable impact on traditional methods of estimation and testing outcomes. Yet, the previous literature does not consider this issue. Alternatively, it is proper to employ stochastic dominance (SD) for testing the SHME because SD accommodates skewness and other data irregularities. SD is free of any assumptions and incorporates information on the entire SV distribution (Sriboonchitta et al., 2010). The use of SD helps us rank the SDs with different maturities to examine the SHME.

In short, this paper contributes and exhibits an innovative way to re-examine the SHME. This paper includes five types of energy futures price series for almost three decades of daily data. SV is adopted as the uncertainty measure and SD is implemented to revisit the SHME. The empirical analysis of the outcomes generally provide mild support to the SHME. SD testing outcomes are contingent on the SV levels. The SHME is more likely to be supported in a series with a low SV level. The SHME does not necessarily hold for higher SV levels, especially at critical market moments. This paper contributes the literature by re-examining the SHME in detail from a novel perspective based on SV and SD.

The rest of the paper is structured as follows: Section 2 reviews the SV model. Section 3 outlines SD. Section 4 describes the data source and discusses the empirical results. Section 5 concludes.

2. A brief review of stochastic volatility models

Tsay (2010) highlights that while uncertainty in volatility is important, it is often overlooked. The SV models outperform ARCH and GARCH models in terms of capturing the higher orders of moments of a volatility model. The GARCH model is designed to model the volatility process in a deterministic model specification. Alternatively, the SV model captures the volatility process in a probabilistic manner (Kastner, 2016). That is, the SV model describes the volatility process through a state-space model in which the latent states are represented by the logarithm of the squared volatilities and follows an autoregressive process of order one. Kim et al. (1998) conclude that, in practice, SV models outperform GARCH models. SV models postulate that volatility is driven by its own stochastic process. SV models under the continuous-time framework are known for capturing some stylized features of financial data (Han et al., 2014). Shephard and Andersen (2009) summarize the advantages of SV models over GARCH models. For example, SV models can approximate the return distributions by a mixture of distributions where the mixture reflects the level of activity or news arrival. A SV model can also accommodate an asymmetric return–volatility relation. These advantages are influential in modeling the uncertainty level. This paper thus selects SV as the criterion for empirical examination.

There are two major estimation methods for SV models: moment methods and simulation methods. While the former are often simpler, they are inefficient. The latter attempt to achieve a close approximation of the likelihood function through computationally expensive simulation methods (Bauwens et al., 2012). To overcome intractability of the likelihood function for SV parameter estimation, MCMC is introduced