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Granger causality in risk and detection of extreme risk spillover between financial markets

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ABSTRACT

Controlling and monitoring extreme downside market risk are important for financial risk management and portfolio/investment diversification. In this paper, we introduce a new concept of Granger causality in risk and propose a class of kernel-based tests to detect extreme downside risk spillover between financial markets, where risk is measured by the left tail of the distribution or equivalently by the Value at Risk (VaR). The proposed tests have a convenient asymptotic standard normal distribution under the null hypothesis of no Granger causality in risk. They check a large number of lags and thus can detect risk spillover that occurs with a time lag or that has weak spillover at each lag but carries over a very long distributional lag. Usually, tests using a large number of lags may have low power against alternatives of practical importance, due to the loss of a large number of degrees of freedom. Such power loss is fortunately alleviated for our tests because our kernel approach naturally discounts higher order lags, which is consistent with the stylized fact that today's financial markets are often more influenced by the recent events than the remote past events. A simulation study shows that the proposed tests have reasonable size and power against a variety of empirically plausible alternatives in finite samples, including the spillover from the dynamics in mean, variance, skewness and kurtosis respectively. In particular, nonuniform weighting delivers better power than uniform weighting and a Granger-type regression procedure. The proposed tests are useful in investigating large comovements between financial markets such as financial contagions. An application to the Eurodollar and Japanese Yen highlights the merits of our approach.

1. Introduction

Controlling and monitoring financial risk have recently received increasing attention from business practitioners, policy makers and academic researchers. For financial risk management and investment/portfolio diversification, it is important to understand the mechanism of how risk spillover occurs across different markets. When monitoring financial risk, the probability of a large adverse market movement is always of greater concern to practitioners (e.g., Bollerslev (2001)). When they occur, extreme market movements imply change hands of a huge amount of capital among market participants, unavoidably leading to bankruptcies due to various downside constraints. Market participants have been always aware of painful experiences when extreme adverse market movements occur, and their aversion to insolvency-type extreme risk is usually very high (e.g., Campbell and Cochrance (1999)). Large market movements have become commonplace nowadays. Examples include the 1994 Mexico Peso Crisis, the 1994 US bond debacle, the 1997–1998 Asian financial crisis, as well as the bankruptcies of the Long Term Capital Management, Enron, and Worldcom.

Most of the existing literature uses volatility to measure risk and focuses on volatility spillover (e.g., Cheung and Ng (1990, 1996)), Engle et al. (1990), Engle and Susmel (1993), Granger et al. (1986), Hamao et al. (1990), King and Wadhwani (1990), King et al. (1994), Lin et al. (1994) and Hong (2001)). Volatility is an important instrument in finance and macroeconomics. However, it can only adequately represent small risks in practice (e.g., Gourieroux and Jasiak (2001, p. 427)). Volatility alone cannot satisfactorily capture risk in scenarios of occasionally occurring extreme market movements. For example, Longin (2000) and Bali (2000) point out that volatility measures based on asset return distributions cannot produce accurate estimates of market risks during volatile periods. Hong et al. (2004, 2007) also find that the innovation distributions have heavier tails when the interest rate market and the foreign

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exchange market have higher volatilities. Moreover, volatility includes both gains and losses in a symmetric way, whereas financial risk is obviously associated with losses but not profits. Also, practical downside constraints often require asymmetric treatment between potential upside and downside risk. Therefore, a more sensible measure of risk should be associated with large losses, or large adverse market movements.

In econometrics and statistics, left tail probabilities are closely related to the likelihoods of extreme downward market movements (e.g., Embrechts et al. (1997)). Although not a perfect measure of extreme market risk, Value at Risk (VaR), originally proposed by J.P. Morgan in 1994, has become a standard synthetic measure of extreme market risk (e.g., Duffie and Pan (1997) and Engle and Manganelli (2004)). It measures how much a portfolio can lose within a given time period, with a prespecified probability. It has become an essential part of financial regulations for setting risk capital requirements so as to ensure that financial institutions can survive after a catastrophic event (e.g., the Basel Committee on Banking Supervision (1996); Basel Committee on Banking Supervision (2001)).[1] Intuitively, VaR measures the total risk in a portfolio of financial assets by summarizing many complex undesired outcomes in a single monetary number. It naturally represents a compromise between the needs of different users. The conceptual simplicity and compromise have made VaR the most popular measure of risk among practitioners in spite of its weakness.[2]

In this paper, we will develop econometric tools for investigating comovements of large changes between two time series. A leading motivating example is the spillover of extreme downside movements between financial markets when markets are integrated and suffer from the same global shock, or due to "market contagion". Using VaR as a measure of extreme downside market risk, we first introduce a new concept of Granger causality in risk, where a large risk is said to have occurred at a prespecified level if actual loss exceeds VaR at the given level. As is well-known, Granger causality (Granger, 1969, 1980) is not a relationship between "causes"and "effects". Instead, it is defined in terms of incremental predictive ability. This concept is suitable for the purpose of predicting and monitoring risk spillover and can provide valuable information for investment decisions, risk capital allocation and external regulation. We then propose a class of econometric procedures to detect Granger causality in risk between financial markets. Utilizing the most concerned information, it checks whether the past history of the occurrences of large risks in one market has predictive ability for the future occurrences of large risks in another market. We emphasize that the scope of the applicability of the concept of Granger-causality in risk is not limited to financial markets and financial positions (e.g., investment portfolios). For example, it can also be used to investigate the spillover of international business cycles, where the understanding of the mechanism of how a large negative shock transmits across different economies is vital to international policy coordination to alleviate its adverse impact on the world economy.

Our proposed procedure has a number of appealing features. First, it checks an increasing number of lags as the sample size T grows. This ensures power against a wide range of alternatives of extreme downside risk spillover. Secondly, our frequency domain kernel-based approach naturally discounting higher order lags alleviates the loss of a large number of degrees of freedom and thus enhances good power of the test, which many chi-square tests with a large number of lags (e.g., Box and Pierre's (1970) portmanteau test) suffer. Downward weighting for higher order lags is consistent with the stylized fact that today's financial markets are often more influenced by the recent events than by the remote past events. Indeed, simulation shows that nonuniform weighting is more powerful than uniform weighting and a Granger-type regression-based procedure. Finally, our procedure is easy to implement, particularly since the VaR calculation has been available in the standard toolbox of risk managers' desk.

In Section 2, we describe the concept of Granger causality in risk and discuss its differences from the concepts of Granger causality in mean (Granger, 1969), Granger causality in variance (Granger et al., 1986) and general Granger causality (Granger, 1980). In Section 3, we use a cross-spectral approach to test one-way Granger causality in risk. The kernel method is used. Section 4 develops the asymptotic theory, and Section 5 considers extensions to bilateral Granger causalities in risk. In Section 6, a simulation study examines the finite sample performance of the proposed procedures. Section 7 presents an empirical application to the Eurodollar and the Japanese Yen. It is found that a large downward movement in the Eurodollar Granger-causes a large downward movement in the Japanese Yen, and the causality is stronger for larger movements. On the other hand, Granger causality in risk from the Japanese Yen to the Eurodollar is much weaker or nonexistent. Section 8 concludes the paper. All mathematical proofs are collected in the Appendix. Throughout, Δ and Δ_0 denote bounded constants; $\to^d$ and $\to^p$ convergences in distribution and in probability respectively; and $\|A\|$ the usual Euclidean norm of A. Unless indicated, all limits are taken as the sample size $T \to \infty$. A GAUSS code for implementing the proposed procedures is available from the authors.

2. Granger causality in risk

2.1. Extreme downside market risk and Value at Risk

For a given time horizon τ and confidence level $1-\alpha$, where $\alpha \in (0, 1)$, VaR is defined as the loss over the time horizon τ that is not exceeded with probability $1-\alpha$. Statistically speaking, VaR, denoted by $V_t \equiv V(I_{t-1}, \alpha)$, is the negative α-quantile of the conditional probability distribution of a time series Y_t (e.g., portfolio return), which satisfies the following equation:

$$P(Y_t < -V_t | I_{t-1}) = \alpha \quad \text{almost surely (} a.s.\text{)}, \tag{2.1}$$

where $I_{t-1} \equiv \{Y_{t-1}, Y_{t-2}, \ldots\}$ is the information set available at time $t-1$. In financial risk management, the left tail probability in (2.1) is usually called the shortfall probability. For notational simplicity, we have suppressed the dependence of V_t on level α. In practice, commonly used levels for α are 10%, 5% or 1%.

To gain insight into VaR from a statistical perspective, we write the time series $\{Y_t\}$ as follows:

$$\begin{cases} Y_t = \mu_t + \sigma_t \varepsilon_t, \\ \{\varepsilon_t\} \sim \text{m.d.s. } (0, 1) \text{ with conditional CDF } F_t(\cdot), \end{cases} \tag{2.2}$$

where $\mu_t \equiv \mu_t(I_{t-1})$ and $\sigma_t^2 \equiv \sigma_t^2(I_{t-1})$ are the conditional mean and conditional variance of Y_t given I_{t-1} respectively, and $F_t(\cdot) \equiv F_t(\cdot|I_{t-1})$ is the conditional cumulative distribution function (CDF) of ε_t given I_{t-1}. By definition, the standardized innovation $\{\varepsilon_t\}$ is a conditionally homoskedastic martingale difference sequence (m.d.s.) with $E(\varepsilon_t|I_{t-1}) = 0$ a.s. and $\text{var}(\varepsilon_t|I_{t-1}) = 1$ a.s., but its higher order conditional moments, such as skewness and kurtosis, may be time-varying. An example is Hansen's (1994) autoregressive conditional density model where $\{\varepsilon_t\}$ follows a generalized Student-t-distribution with time-varying shape parameters.

From (2.1) and (2.2), we obtain the VaR

$$V_t = -\mu_t + \sigma_t z_t(\alpha), \tag{2.3}$$

where $z_t(\alpha) \equiv z(I_{t-1}, \alpha)$ is the left-tailed critical value at level α of the conditional distribution $F_t(\cdot)$ of ε_t; that is, $z_t(\alpha)$ satisfies

[1] VaR is a measure of extreme downside risk and is similar in methodology to lower partial moments in the earlier literature (e.g., Roy (1952)).

[2] For example, Artzner (1999) defines certain properties that a good risk measure should have and shows that VaR does not satisfy all of them. Many other kinds of risk measures have been proposed but none gained the popularity as VaR.