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Translating financial integration into correlation risk: A weekly reporting's viewpoint for the volatility behavior of stock markets

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ABSTRACT

We apply the multivariate extension of GARCH-type models in order to assess the systematic and systemic risks as well as the joint volatility behaviors of the U.S. and three European financial markets (Andersen et al., 2010). Therefore, we can appraise the co-movements of the four previous financial markets as well as the joint behavior of their respective volatilities (i.e. systemic risk). Moreover, the resulting conditional variance and covariance metrics allow for handling volatility spillovers (i.e. contagion risk in terms of transmitting volatility shocks from one market place to another market place). Indeed, results highlight the unprecedented high systemic risk levels (i.e. joint increased volatility levels) as well as a high contagion risk (i.e. volatility spillover) during the subprime mortgage market crisis. The transmission process of volatility shocks reveals to be simultaneous across financial markets due to a strong arbitrage activity and electronic trading practices among others. Most importantly, the estimated conditional correlations exhibit an upward sloping trend, which underlines an increase in the correlation risk between financial markets in the late nineties or early 2000. Thus, our major findings are twofold. First, we characterize the dynamic correlation risk across financial markets. Second, we also confirm the increasing and nonlinear trend in the correlation risk, which we are able to quantify.

1. Introduction

The recent financial and credit crises shed light on the integration level and the volatility transmission pattern of financial markets (i.e. volatility spillovers). Indeed, the global market view is important insofar as it targets the well-known systemic risk as illustrated by the common reaction of several market places over time (i.e. market co-movements).[1] Such a common behavior is all the more exacerbated during times of high volatility so that systematic and/or systemic risk prevails and portfolio diversification possibilities reduce dramatically.[2] Hence, the temporal dependence of market volatility, also known as volatility clustering, as well as the joint behavior of market volatilities have become a huge challenge during the past recent years. Specifically, volatility describes the magnitude with which financial prices tend to move. Large volatility levels illustrate important price moves (i.e. disturbed market times) whereas small volatility levels illustrate stable market behaviors. Therefore, volatility reflects prices' or returns' uncertainty over time and represents a significant risk measure. The main problem relies on the choice of a relevant/consistent volatility measure, or equivalently, the manner with which volatility is assessed (Andersen et al., 2006). Such a concern is of huge significance for the portfolio management industry, risk hedging activity, risk measures' reliability (e.g. value-at-risk computations) and derivative pricing (Brooks and Persand, 2003). Specifically, value-at-risk metrics are strongly dependent on volatility measurement.

The well-known volatility clustering pattern exhibits the temporal dependence in the financial market's volatility over time. In particular, high volatility levels tend to be followed by other high volatility levels, and the same principle applies to low volatility levels. Therefore, volatility is a time-varying risk measure. Often, the squared returns of traded financial assets are employed as a proxy of time-varying variance (i.e. volatility) but such a proxy is also known to be noisy and difficult to employ in a forecasting viewpoint (Hansen and Lunde, 2006; McAleer and Medeiros, 2008b). As a consequence, a more sophisticated tool is required to assess the dynamic of returns' uncertainty (Andersen and Bollerslev, 1998; Engle, 1982; Engle and Patton, 2001). Autoregressive conditional heteroskedastic (ARCH) as well as generalized autoregressive conditional heteroskedastic (GARCH) models among others bring an interesting answer to this problem (Bollerslev, 1986; Bollerslev and Engle, 1993; Bollerslev et al., 1992, 1994; Engle, 1982; Nelson, 1990a,b, 1991, 1992). Specifically, the previous approaches yield one relationship describing the trend of a given financial market, and one explicit

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[1] Co-movements refer to the propensity of financial assets to evolve in the same way (e.g. prices evolve in the same direction) at more or less the same time. But, there may be a delay in between the times at which two markets move in the same way.

[2] Basically, systematic risk refers to the risk borne by the set of all the financial assets, which are traded on the same market place (i.e. within the same Stock Exchange of a given country). In a broader view, systemic risk refers to the risk borne by the financial assets, which are traded on the global market place (i.e. it concerns the Stock Exchanges of all the countries). In particular, it is a worldwide risk.

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relationship describing the financial market's volatility (i.e. variance). Hence, both the market trend and its corresponding volatility pattern are simultaneously accounted for over time. For that reason, we employ the multivariate extension of GARCH models to assess the systematic and systemic risks as well as the joint volatility behaviors of the U.S. and three European financial markets (Andersen et al., 2010). Thus, we can assess the co-movements of the previous financial markets as well as the joint behavior of their respective volatilities (i.e. systemic risk). Moreover, the resulting conditional variance and covariance metrics allow for handling volatility spillovers. And, volatility spillovers reflect a contagion risk in terms of transmitting volatility shocks from one market place to another market place (Degryse et al., 2010; Dungey and Yalama, 2010). Specifically, a financial contagion phenomenon refers to the propensity of stock returns to move together with an extreme magnitude at more or less the same time or within a very short time window (Longstaff, 2010).

In this article, we propose therefore to examine how the degree of financial integration of the U.S. and European markets translates into joint correlation risks (Claessens et al., 2012; Mendoza et al., 2009). Incidentally, financial integration refers to the various linkages between different market places and related regional commonalities among which are trade, direct investment, de/regulation, banking linkages and market liberalization. Consequently, it refers to the propensity of financial markets to move in the same direction (i.e. systemic risk) with more or less the same magnitude of moves (i.e. volatility contamination). Investigating the correlation risk in the lens of financial integration is crucial to portfolio diversification rules and risk management practices such as value-at-risk. Under such a setting, our study's added value is threefold. First, we describe the trend of financial markets through relevant mean equations, which integrate the information brought in by implied market volatility indexes. Therefore, we describe the level of systematic risk, which is peculiar to each financial market under consideration. Moreover, the systematic risk analysis is also complemented by a complementary measure of market-specific conditional variances through a consistent multivariate variance equation. Second, we characterize the correlation risk, or equivalently, the systemic risk of financial markets through consistent conditional correlation metrics. The dynamic correlation risk structure is therefore emphasized and the asymmetric impact of bad news on stock market returns' levels and risk (as represented by variance and correlation metrics) is also accounted for. Finally, we exhibit the nonlinear and upward sloping trend in the level of the conditional correlations between the U.S. and the three European financial markets under consideration. Such a broad trend emphasizes an increase in the general level of correlation risk, which we are able to characterize. In this prospect, our paper is organized as follows. Section 2 introduces the data under consideration as well as their statistical and distributional properties. Data are considered on a weekly basis so as to focus on a weekly risk reporting in accordance with the risk management practices of the banking industry for example. Moreover, the weekly setting also conforms to risk management practices, which rely on a weekly horizon with respect to value-at-risk estimates. While introducing a risk management tool, Section 3 presents the selected multivariate GARCH model, the rationale as well as the empirical facts supporting such a model, and the corresponding results. The general behavior of conditional correlations is also investigated over time through the nonparametric regression methodology. In particular, we investigate and characterize the general behavior of joint risk levels. Finally, Section 4 concludes and proposes possible extensions in the light of the dynamic correlation risks across financial markets.

2. Data

We target to study the joint behavior of the U.S. financial market on one side, and the German, French and English financial markets on the other side. Our interest focuses on both market trends and volatility/variance behaviors. As an example, Claessens et al. (2012) explain that the level of financial integration has increased among developed economies so that U.S. and European countries are financially integrated. Therefore, shocks to the U.S. financial market and U.S. economy propagate to other countries such as the developed European countries.

2.1. Presentation

Given the financial markets under consideration, we consider both the percentage logarithmic returns (i.e. log-returns) of their respective stock market indexes and the changes in their corresponding implied volatility indexes (see Table 1). Stock indexes are primary market trend indicators whereas implied volatility indexes bring in complementary trend information. In particular, stock index returns illustrate directional market moves whereas changes in implied volatility indexes reflect the magnitude of such moves. Furthermore, implied volatility indexes usually serve as a fear gauge and help explain market psychology and shifts as well as risk expectations. Our data are taken on a weekly basis from Reuters data provider, and computed from end-of-the-week closing prices and index values (i.e. last available price of any week). Hence, there is a highly reduced asynchronous trading problem to handle with respect to the frequency of data. The time span under consideration runs from 06/14/1992 to 04/25/2010, so that we consider 933 observations per data series.[3]

As a consistency test, we report in Table 2 the correlation matrix between our data. All the displayed Kendall and Spearman correlation coefficients are significant at a one-percent two-tailed Student test level.

As expected, implied volatility changes are significantly and negatively correlated with log-returns so that they are considered as complementary explanatory factors. Despite its reported upward bias (Doran and Ronn, 2005; Dowling and Muthuswamy, 2005), implied volatility brings in some additional information about market returns (Christensen and Prabhala, 1998; Ederington and Guan, 2002).[4] On an average basis, the negative link associates poor market returns with high implied volatility levels whereas low implied volatilities are associated with performing market returns. Such results support the asymmetric market reaction to bad news (Black, 1976; Fornari et al., 2002), which is also known as the leverage effect. In unreported results, we first tested for the stationary pattern in our market data. Both volatility index changes and market index log-returns exhibit a stationary behavior at a one percent level of Phillips–Perron test without trend and without constant. We also controlled for corresponding autocorrelations and partial autocorrelations as well as related Ljung–Box statistics. Index log-returns and implied volatility changes are serially dependent over time (i.e. autocorrelation prevails).

2.2. Properties

2.2.1. Descriptive statistics

As a preliminary investigation, Table 3 displays all the relevant descriptive statistics. Obviously, index log-returns are leptokurtic (i.e. negative skewness and positive excess kurtosis). Basically, left-asymmetry illustrates more below-average log-returns than above-average ones. Differently, the positive excess kurtosis highlights the presence of a fatter tail as compared to the corresponding Gaussian distribution. On another hand, changes in volatility indexes exhibit a positive skewness (i.e. right tail) and also a positive excess kurtosis (i.e. fatter tail than the Gaussian distribution). Therefore, there exist more above-average volatility changes as compared to below-average ones. Such a

[3] Initially, index prices and implied volatility levels are considered from 06/07/1992 up to 04/25/2010, namely a total of 934 observations per series.

[4] Frijns et al. (2010) underline that a systematic and known bias in a volatility measure is not an issue since such a bias can be controlled. However, the volatility measure under consideration needs to be a good forecaster/predictor (i.e. exhibiting a high R-square).