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A cross-volatility index for hedging the country risk

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ABSTRACT

This paper proposes a new empirical methodology for computing a cross-volatility index, coined CVIX, that characterizes the country risk understood here as the financial market risk measurement. The approach, based on the Factor DCC-model, requires to encapsulate all the sources of risk stemming from the financial markets for any given country. We provide an application to the U.S. economy by constructing an aggregate volatility index composed of implied volatility indexes characterizing the equity market, the FX market, fixed income market and the commodity market. The analysis reveals that 75% of the aggregate risk comes from the commodity market, and that the volatility index average value evolves around 22%. The CVIX provides a better hedging performance than the VVIX used as a benchmark.

1. Introduction

The motivation of this paper is to propose an empirical methodology to construct a volatility index that reflects the main sources of risks for any given country. The country risk refers to the fact of investing in a country, where the risk is dependent on changes in the macroeconomic and business environments affecting any of its financial markets (see Liu et al. (2013) for a recent application to the BRICS). The increasing globalization has substantially raised the exposure of investors to risks related to events in various countries. In that context, international investment requires more attention to risk analysis and risk hedging (for a more theoretical discussion see Eaton (1986), and more generally see Saini (1984), Cosset (1992), Oetzel et al. (2001), Hassan et al. (2003), Andrade (2009) and recently Agliardi et al. (2012)). Unfortunately, there seems to be missing in the literature a strategy for hedging directly the volatility risk. Therefore, the construction of an aggregate volatility index appears important, since it provides an investor with a unique hedging instrument to mitigate, if not cancel, the country risk. These risks arise from all the markets, namely, equities, interest rates, foreign exchange and commodities. To achieve this goal, we need to build a cross-volatility index, that requires an appropriate methodology for computing multivariate correlations.

Nevertheless, carrying out this research task is not trivial for three reasons. The first problem lies in determining the correct correlation function that captures precisely the time-varying nature of market data. Second, the econometrician is

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faced with the choice of the proper methodology to estimate loading factors from market data. Third, there is a concern about the arbitrary choice of the number of factors.

This paper reconciliates all three issues by following and enriching the Factor-DCC methodology by Zhang and Chan (2009). Their model dramatically simplifies the estimation process by estimating the correlation function on a small number of factors instead of multiple pairwise DCCs. Factor methods arise from the need for economists to follow several time-series variables as proxies for the state of the economy. Thus, it appears necessary to gather as much information as possible from as many variables as possible. To that end, factor models have been developed to extract the information in datasets with many variables while, at the same time, keeping the model parsimonious (see Stock and Watson (2005, 2006) for a survey).

However, as Zhang and Chan (2009) allow an arbitrary choice of factors that enters the computation of the Factor-DCC model, we complement their methodology by implementing an optimal criterion that reduces this number of factors. This automated approach avoid any subjective interpretation likely to induce any kind of statistical bias.

The empirical application is based on a dataset of 10 implied volatility indexes from the CBOE and CBOT. We believe that implied volatility measures of various financial securities adequately capture the essentially political nature of country risk. Since the political risk intrinsic to each country is reflected in its interest rate, investors on efficient markets include a political risk premium in the domestic financial assets, especially when lending money. Therefore, the implied volatility of the interest rate, more than other indicators, is able to price the country risk better than a rating agency would.

Our central contribution consists in setting up an empirical methodology that combines the Factor-DCC methodology with an automated factors detection in order to create a cross-volatility index, coined CVIX, which serves for hedging the country risk at an aggregate level. An application is provided on the U.S. market. To our best knowledge, the Factor-DCC approach has never been implemented by mixing volatilities stemming from commodity markets with traditional financial asset volatilities (foreign exchange, bonds and equities). This cross-volatility index is far more representative of the country risk than classical financial indexes. Our main results may be summarized as follows. First, financial securities only represent 25% of the global risk in the index. Second, the CVIX is sensitive to each market swings, by construction. Third, we evaluate the efficiency of the newly constructed index with the CBOE VIX index as a benchmark. The VIX is taken here as a global risk indicator from which hedging strategies can be derived. Typically, the hedging performance of our index appears to be superior. Investors facing a domestic risk should be inclined to use the CVIX to hedge their position.

The Factor-DCC works in a two-step fashion: (i) two factors are extracted based on principal component analysis, and (ii) the time-varying conditional correlation between the estimated factors is estimated. Is this methodology new? Yes, simply because the principal components approach is a static computation yielding factors that are de-correlated on average, but not dynamically. Therefore, static principal components only could be exposed to a risk of re-correlation between factors during a given period (say, a crisis period) inducing a less efficient volatility index. By using the Factor-DCC approach, we ensure that the dynamic conditional correlation trend between factors remain close to zero despite some temporary peaks and troughs. Specifically, we check that the trend remains in the neighborhoods of zero as requested. It can be seen as an *ex-post* inspection/validation.

We choose this methodology to create the CVIX in order to meet the needs of asset managers to follow several time series at a time. Sometimes a dozen, sometimes a hundred as in contemporary macroeconomics and central banking. That is why it is crucial to rely on this method in order to compute the CVIX. It allows to compute time-varying conditional correlations between factors (which themselves synthesize the information from several time series), instead of the limitations of the traditional DCC model (where only pairs of variables can robustly be estimated at a time, see Caporin and McAleer (2014)). In our application, we deal with a high-dimensional data problem, since we consider 10 time series at a time (e.g. a standard DCC would have implied the study of $n(n-1)/2 = 45$ pairs.

The remainder of the article is structured as follows. Section 2 details the Factor-DCC methodology. Section 3 describes the dataset. Section 4 contains the empirical results, and details the composition of the CVIX. Section 5 concludes.

2. The Factor DCC model

2.1. The methodology

Zhang and Chan (2009) have adapted factor modeling techniques to the field of financial econometrics, with the inclusion of time-varying conditional correlations that are essential to capture the key trends in time series data. In their article, the authors use standard static Principal Components (PC) methods to extract two factors, by following the classical approach suggested by Stock and Watson (2002a,b). The use of PC methods ensures the identification of the model, since it normalizes all factors to have mean zero and variance one (Forni et al., 2000), Bai and Ng (2007)). Besides, the empirical implementation of the Factor-DCC model proceeds with PC estimates, due to their relative computational tractability.[1] To our best knowledge, no statistical tests have been implemented to determine the number of factors in a Factor-DCC. In their empirical application to the Hong Kong stock market, Zhang and Chan (2009) allow an arbitrary choice of factors that enters the computation of

[1] Alternative methods involve Markov chain Monte Carlo (MCMC) estimation of dynamic factors using the Kalman filter. Besides their heavy computational burden, they require strong identification restrictions which may lead to factors with poor economic content. Hence, our choice of the PC methods.