Journal of Financial Markets 37 (2018) 97–119

Contents lists available at ScienceDirect

Journal of Financial Markets

journal homepage: www.elsevier.com/locate/finmar

Do co-jumps impact correlations in currency markets? ☆

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ARTICLE INFO

Article history:
Received 17 February 2016
Received in revised form 20 November 2017
Accepted 20 November 2017
Available online 23 November 2017

JEL classification:
C14
C53
G17

Keywords:
Co-jumps
Currency markets
Realized covariance
Wavelets
Bootstrap

ABSTRACT

We quantify how co-jumps impact correlations in currency markets. To disentangle the continuous part of quadratic covariation from co-jumps, and study the influence of co-jumps on correlations, we propose a new wavelet-based estimator. The proposed estimation framework is able to localize the co-jumps very precisely through wavelet coefficients and identify statistically significant co-jumps. Empirical findings reveal the different behaviors of co-jumps during Asian, European, and U.S. trading sessions. Importantly, we document that co-jumps significantly influence correlation in currency markets.

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1. Introduction

One of the fundamental problems faced by a researcher trying to understand financial markets is how to quantify the interdependence of assets. Although commonly used correlation-based measures are essential tools used to uncover the interdependence structures, exogenous events resulting in idiosyncratic and systemic jumps, or co-jumps, may impact the measurements. Being equally important part of the information, co-jumps and their role need to be understood fully before making any conclusions about interdependence. In this paper, we focus on estimating the effects of these exogenous events to see how co-jumps impact correlations in currency markets. Since correlation is covariance normalized by variance, we propose a wavelet-based framework to accurately estimate total covariance, as well as disentangle the continuous from discontinuous (co-jump) part of covariation. Having the decomposition in hand, we define the continuous correlation as a measure that is not dependent on important market announcements (co-jumps) or extreme univariate shocks of the single

☆ We are grateful to the editor Tarun Chordia and an anonymous referee for useful comments and suggestions, which have greatly improved the paper. Furthermore, we are indebted to Torben Andersen, Ionut Florescu, Giampiero Gallo, Karel Najzar, Roberto Renò, David Veredas, and seminar participants at the Vienna-Copenhagen Conference on Financial Econometrics (Vienna, 2017), 69th European meeting of the Econometric Society (Geneva, 2016), Conference on Financial Econometrics and Empirical Asset Pricing (Lancaster, 2016), Modeling High Frequency Data in Finance (New York, 2015), Non- and Semiparametric Volatility and Correlation Model (Paderborn, 2014), and Computational and Financial Econometrics in London (London 2011) for many useful comments, suggestions, and discussions. Support from the Czech Science Foundation under the GA16-14151S project is gratefully acknowledged.

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https://doi.org/10.1016/j.finmar.2017.11.004
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asset (jumps). Comparing the total and continuous correlations, we answer the question how co-jumps impact correlations on currency markets. In addition, we document the co-jump, covariance, and correlation dynamics for the three main trading sessions—Asia, Europe, and the United States—to determine where the dependence is being created.

Distinguishing between continuous and co-jump covariation is important for asset pricing as both parts carry different sources of risk leading to different optimal hedging strategies in asset pricing models (Aït-Sahalia and Jacod, 2009). While the continuous covariation part of asset components can be well diversified in the portfolio, the presence of co-jumps implies that the construction of a hedging portfolio has to consider new constraints (Mancini and Gobbi, 2012). Moreover, separating the contribution of continuous and (co-)jump covariation in asset prices is crucial for investors. For example, the correlation between an asset and the stock market is an essential part of the capital asset pricing model (CAPM). Hence, an increase in total correlation due to the presence of co-jumps will increase market price risk, or beta, and an investor needs to be aware of this to be able to price this part of financial risk.

Modeling the covariance structures has received considerable attention in the literature. With increased availability of high-frequency intraday data, the literature has shifted from parametric conditional covariance estimation toward model-free measurement. This paradigm shift from treating covariances as latent towards directly modeling expost covariance measures constructed from intraday data (Andersen et al., 2003; Barndorff-Nielsen and Shephard, 2004b) has spurred additional interest. Although the theory is appealing and intuitive, it assumes that the observed high-frequency data represent the underlying process. Nevertheless, the real-world data contains microstructure noise and jumps, which makes drawing statistical inferences rather difficult.

To address the presence of microstructure noise, researchers often collect sparsely sampled observations. This approach reduces the bias due to noise, but discards a very large amount of data directly. Although it is statistically implausible, the reason is based on an empirical observation of increasing biases with increasing data-collection frequency. The desire to use all available data at higher frequencies has led to a number of proposed approaches to restore consistency through subsampling, for example, Zhang's et al. (2005) two-scale realized volatility estimator. Zhang (2011) generalizes these ideas to a multivariate setting and defines a two-scale covariance estimator. Barndorff-Nielsen et al. (2011) achieve positive semi-definiteness of the variance-covariance matrix using multivariate kernel-based estimation. Furthermore, Aït-Sahalia et al. (2010) and Griffin and Oomen (2011) address microstructure noise and non-synchronous trading and propose a consistent and efficient estimator of realized covariance. Aït-Sahalia and Jacod (2012) analyze the effects of microstructure noise and jumps, and Varneskov (2016) estimate quadratic covariation using a general multivariate additive noise model.

In addition to the microstructure noise, ignoring jumps and co-jumps can substantially influence the results of estimation, especially with regard to forecasting, option pricing, portfolio risk management, and credit risk management (Jawadi et al., 2015). Building on univariate jump detection,[1] the literature has lately focused on detecting co-jumps and multi-jumps. Bollerslev et al. (2008) detect co-jumps in a large panel of intraday stock returns in an equally-weighted portfolio. They propose a mean cross-product statistic that directly measures how closely the stocks co-move. Lahaye et al. (2011) use Lee and Mykland's (2008) univariate jump test to identify co-jumps, defined as jumps occurring simultaneously on different markets. They call this approach "univariate co-jumps" because their detection relies on univariate jump detection. In addition, Mancini and Gobbi (2012) observe co-jumps via thresholding techniques. Recently, spectral techniques for co-jump detection have been employed by Bibinger and Winkelmann (2015). Gilder et al. (2014) use the approach of Bollerslev et al. (2008) to identify co-jumps at daily frequency. Because this method is not robust against disjoint co-jumps, these authors further utilize tests for intraday jumps, as described by Andersen et al. (2010). Boudt and Zhang (2015) propose a jump robust version of Zhang's (2011) two-scale covariance estimator. A test statistic that can explicitly identify co-jumps is proposed in Gnabo et al. (2014) and accounts for the assets' covariation, considering a co-jump as a large cross product of returns with respect to local covariation. A common problem associated with this method is that it can lead to false co-jump detection when a substantially large jump occurs in only one asset. Extension to a multivariate space is proposed by Caporin et al. (2016), who use a formal test to detect multi-jumps in larger portfolios. Their procedure is based on comparing two types of smoothed power variations.

In this study, we contribute to the growing literature by introducing an approach based on a wavelet decomposition of stochastic processes. The main reason why we focus on wavelet analysis is its remarkable ability to detect jumps and sharp cusps even if covered by noise (Donoho and Johnstone, 1994; Wang, 1995). Several authors have used these results to improve the jump estimation (Fan and Wang, 2007; Xue et al., 2014; Barunik and Vacha, 2015; Barunik et al., 2016). The reported improvements originate from the fact that wavelets are able to decompose noisy time series into separate time-scale components. This decomposition then helps to distinguish jumps from continuous price changes, and microstructure noise effects as wavelet coefficients decay at a different rate for continuous and jump processes. Wavelet coefficients at jump locations are larger in comparison to other observations. While changes in continuous price processes over a given small time interval are close to zero, changes in jumps are not. Wavelet coefficients are able to precisely distinguish between these situations, and hence locate jumps very precisely. Specifically, the first scale wavelet coefficients represents only the highest frequency, thus they can detect sharp discontinuities in the process without being influenced by other frequency components.

[1] The univariate jump detection is addressed, for example, in Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007), Lee and Mykland (2008), Aït-Sahalia and Jacod (2009), Jacod and Todorov (2009), and Novotný et al. (2015), among others.

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