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# Realized jumps on financial markets and predicting credit spreads[☆]

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ABSTRACT

This paper extends the jump detection method based on bipower variation to identify realized jumps on financial markets and to estimate parametrically the jump intensity, mean, and variance. Finite sample evidence suggests that the jump parameters can be accurately estimated and that the statistical inferences are reliable under the assumption that jumps are rare and large. Applications to equity market, treasury bond, and exchange rate data reveal important differences in jump frequencies and volatilities across asset classes over time. For investment grade bond spread indices, the estimated jump volatility has more forecasting power than interest rate factors and volatility factors including option-implied volatility, with control for systematic risk factors. The jump volatility risk factor seems to capture the low frequency movements in credit spreads and comoves countercyclically with the price–dividend ratio and corporate default rate.



## 1. Introduction

The relatively large credit spread on high grade investment bonds has long been an anomaly in financial economics. Historically, firms that issue such bonds appear to entail very little default risk yet their credit spreads are sizable and positive (Huang and Huang, 2003). A natural explanation is that these firms are exposed to large sudden and unforeseen movements in the financial markets. In other words, the spread accounts for exposure to market jump risk. Jump risk has been proposed before as a possible source of the credit premium puzzle (Delianedis and Geske, 2001; Zhou, 2001; Huang and Huang, 2003), but the empirical validation in the literature has met with mixed and inconclusive results (Collin-Dufresne et al., 2001, 2003; Cremers et al., 2004, in press). In this paper, we develop a jump risk measure based on identified realized jumps (as opposed to latent or implied jumps) as an explanatory variable for high investment grade credit spread indices.

The continuous-time jump–diffusion modeling of asset return processes has a long history in finance, dating back to at least Merton (1976). However, the empirical estimation of the jump–diffusion processes has always been a challenge to econometricians. In particular, the identification of actual jumps is not readily available from the time series data of underlying asset returns. Most of the econometric work relies on some combination of numerical methods, computationally intensive simulation-based procedures, and possibly joint identification schemes from both the underlying asset and the derivative prices (see, e.g., Bates, 2000; Andersen et al., 2002; Pan, 2002; Chernov et al., 2003; Eraker et al., 2003, among others).

This paper takes a different and direct approach to identify the realized jumps based on the seminal work by Barndorff-Nielsen and Shephard (2004, 2006). Recent literature suggests that the realized variance measure from high frequency data provides an accurate measure of the true variance of the underlying continuous-time process (Barndorff-Nielsen and Shephard, 2002a; Meddahi, 2002; Andersen et al., 2003b). Within the realized variance framework, the continuous and jump part contributions can be separated by comparing the difference between realized variance and bipower variation (see Barndorff-Nielsen and Shephard, 2004; Andersen et al., 2004; Huang and Tauchen, 2005). Other jump detection methods have been proposed in the literature based on the swap variance contract (Jiang and Oomen, 2005), the range statistics (Christensen and Podolski, 2006; Dobrislav, 2006),

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and the local volatility estimate (Lee and Mykland, forthcoming). Under the reasonable presumption that jumps on financial markets are usually rare and large, we assume that there is at most one jump per day and that the jump dominates the daily return when it occurs. This allows us to filter out the realized jumps, and further to directly estimate the jump distributions (intensity, mean, and variance). Such an estimation strategy based on identified realized jumps stands in contrast with existing literature that generate noisy parameter estimates based on daily returns.

Aït-Sahalia and Yacine (2004) examines how to estimate the Brownian motion component by maximum likelihood, while treating the Poisson or Lévy jump component as a nuisance or noise. Our approach is exactly the opposite — we estimate the jump component directly and then use the results for further economic analysis. The advantages of this approach include that we do not require the specification and estimation of the underlying drift and diffusion functions and that the jump process can be flexible. Such a jump detection and estimation strategy could be invalid for a certain highly active Lévy process with infinite small jumps in a finite time period (Bertoin, 1996; Barndorff-Nielsen and Shephard, 2001; Carr and Wu, 2004). A recent paper by Aït-Sahalia and Jacod (2006) develops a method for detecting the infinite activity Lévy type jumps from Brownian motions. The approach here is more applicable to the compound Poisson jump process, where rare and potentially large jumps in financial markets are presumably the responses to significant economic news arrivals (Merton, 1976). It should be pointed out that bipower variation also works for the infinite activity jumps (Barndorff-Nielsen et al., 2006; Jacod, in press), although we focus solely on the case of rare and large jumps.

In Monte Carlo work, we examine two main settings where the jump contribution to the total variance is 10% and 80%. In these situations, our realized jump identification approach performs well, in that the parameter estimates are accurate and converge as the sample size increases (long-span asymptotics). One important caveat is that these convergence results depend on choosing appropriately the level of the jump detection test. The significance level needs to be set rather loosely at 0.99 when the jump contribution to the total variance is low (10%), but set rather tightly at 0.999 when the jump contribution is high (80%). Note that a smaller jump contribution like 10% seems to be the main empirical finding in the literature (see Andersen et al., 2004; Huang and Tauchen, 2005, for example).

The proposed jump detection mechanism is implemented for the S&P 500 market index, the ten-year US treasury bond, and the dollar/yen exchange rate, to cover a representative set of asset classes. The jump intensity is estimated to be the smallest for the equity index (13%), but larger for the government bond (18%) and the exchange rate (20%), while the jump mean estimates are insignificantly different from zero. The jump volatility estimates are for the stock market (0.53%), the bond market (0.65%), and the currency market (0.39%). Rolling estimates reveal interesting jump dynamics. The jump probabilities are quite variable for equity index and treasury bond (from 5% to 25%), but relatively stable for dollar/yen currency (20%). Although the jump means are mostly statistically indistinguishable from zero for all assets considered here, there are obvious positive deviations from zero for the S&P 500 index in the late 1990s. Finally, the jump volatilities have not changed much for government bonds, except for a hike in 1994, and the exchange rate, but have increased significantly for the US equity market from 2000 to 2004.

It turns out that the capability of identifying realized jumps has important implications for estimating financial market risk adjustments. For the Moody's AAA and BAA credit spread monthly indices, we find that the rolling estimates of stock market jump volatility can predict the spread variation with $R^2$'s of 0.62–0.66, which are considerably higher than those obtained with the standard interest rate factors, volatility factors including the option-implied volatility, and the systematic Fama-French factors. This result is important, since explaining high investment grade credit spreads has not been very successful and the empirical role of jumps in explaining these credit spreads has largely not been confirmed in the literature so far. Jump volatility remains statistically significant even when the lagged credit spread is controlled for. The market jump risk factor constructed from high frequency data seems to be able to capture the low frequency movements in credit spreads in terms of long-run trend and business cycles. Jump volatility also comoves countercyclically with the price–dividend ratio and corporate default rate, with correlations of 0.67 and 0.65, which has important asset pricing implications along the lines of Bansal and Yaron (2004).

The rest of the paper is organized as follows. The next section introduces the jump identification mechanism based on high frequency intra-day data, then Section 3 provides some Monte Carlo evidence on the small sample performance of such an estimation strategy. Section 4 illustrates the approach with four financial market assets, Section 5 discusses the implications for predicting credit risk spreads, and Section 6 concludes.

## 2. Identifying realized jumps

Jumps are important for asset pricing (Merton, 1976), yet the estimation of jump distribution is very difficult, especially when only low frequency daily data are employed (Bates, 2000; Andersen et al., 2002; Pan, 2002; Chernov et al., 2003; Eraker et al., 2003; Aït-Sahalia and Yacine, 2004). In recent years, Andersen et al. (1998), Andersen et al. (2001, in press), Barndorff-Nielsen and Shephard (2002a,b), and Meddahi (2002) have advocated the use of so-called realized variance measures by utilizing the information in the intra-day data for measuring and forecasting volatilities. More recent work on bipower variation measures developed in a series of papers by Barndorff-Nielsen and Shephard (2003, 2004, 2006) allows for the use of high frequency data to disentangle realized volatility into separate continuous and jump components (see Andersen et al., 2004; Huang and Tauchen, 2005, as well). In this paper, we rely on the presumption that jumps on financial markets are rare and large in order to extract the realized jumps and to explicitly estimate the jump intensity, mean, and volatility parameters. Empirical evidence presented by Lee and Mykland (forthcoming, Table V) is generally supportive of the notion of very rare jumps.

### 2.1. Filtering jumps from bipower variation

Let $p_t = \log(P_t)$ denote the time $t$ logarithmic price of the asset, and assume that it evolves in continuous time as a jump–diffusion process:

$$\mathrm{d}p_t = \mu_t \mathrm{d}t + \sigma_t \mathrm{d}W_t + J_t \mathrm{d}q_t \qquad (1)$$

where $\mu_t$ and $\sigma_t$ are the instantaneous drift and diffusion functions that are completely general and may be stochastic (subject to the regularity conditions), $W_t$ is the standard Brownian motion, $\mathrm{d}q_t$ is a Poisson jump process with intensity $\lambda_J$, and $J_t$ refers to the corresponding (log) jump size distributed as Normal$(\mu_J, \sigma_J)$. Note that this approach can be extended to allow for time variation in jump rates $\lambda_{J,t}$, jump means $\mu_{J,t}$, and jump volatilities $\sigma_{J,t}$, which can be implemented empirically once the actual jumps are filtered out. Time is measured in daily units and the intra-daily returns are defined as follows:

$$r_{t,j} \equiv p_{t,j\cdot\Delta} - p_{t,(j-1)\cdot\Delta} \qquad (2)$$

where $r_{t,j}$ refers to the $j$th within-day return on day $t$, and $\Delta$ is the sampling frequency within each day.