Identifying jumps in intraday bank stock prices: What has changed during the turmoil?

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Abstract

The paper studies jumps in a panel of intraday stock returns of 17 large euro area banks and a portfolio constructed from these stocks. Using a recent non-parametric approach we test for jumps both in individual stocks and in portfolio return, or co-jumps. We pay special attention to the underlying factors that induce jumps both before and after the recent financial crisis that started in the summer of 2007.

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1 Introduction

Banks have been at the epicentre of the recent financial turmoil that started in the summer of 2007. The crisis has particularly hit the banking sector around the world, many banks have suffered huge losses, and some even needed government help to survive. Sharp movements in banks' stock prices can have been observed, and the big uncertainty regarding banks' solvency induced high volatility in financial markets. Since the banking sector (and in general financial services) has accounted for an increasing proportion of the GDP of most developed economies over the last decade, the financial crisis has also had a considerable impact on the real economy, leading to higher unemployment and higher public debt. Moreover, frozen money markets made banks stop lending which led to personal and corporate bankruptcies.

The appropriate response of central banks to such a financial turmoil is still the subject of an important debate. While some recommend the complete separation of monetary policy and financial stability (see Goodhart and Shoenmaker, 1995; and Di Giorgio and Di Nola, 1999), others stress that monetary policy should alleviate financial shocks that hit the financial system. In practice, the latter approach has mostly been adopted, since, for example, the Fed made its sharpest interest rate cuts in response to the most serious financial crises: the October 1987 stock market crash, the 1998 Russian default and the recent crisis, see Goodfriend (2002). In either case, for central banks the study of banks' asset prices is of great interest, since, say, a big drop in a bank's assets may cause bank run and threaten financial stability. Moreover, sharp movements in banks' stock prices may also affect interbank lending rates, leading to the abnormal functioning of money markets, such as a frozen market or a market with very high volatility. Since monetary policy can only directly drive very short rates, such an abnormality reduces significantly the effectiveness of monetary policy.

Therefore, it is of crucial importance to examine the factors underlying sharp movements, or jumps, in banks' stock prices. Jumps also play a big role in investors' asset allocation and in risk management. In a market where big jumps occur occasionally, investors may be more risk averse and avoid trading. Moreover, since jumps are unpredictable, it is impossible to hedge against them by any portfolio, created by the underlying asset, spot and/or derivatives contracts. The characterisation of the jump distribution and the factors underlying jumps can also improve asset pricing, as pointed out by Tauchen and Zhou (2005) and Lee and Mykland (2008).

The objective of this paper is to study jumps in intraday stock returns of 17 large euro area banks. Since the sample period includes the recent financial crisis, we can compare the characteristics of the jump distribution before and after the turmoil as well as the underlying factors that induced jumps in the two subsamples. Since our sample contains both banks that have got into trouble and others that have not been affected by the turmoil, the analysis can provide some insight into the different reactions of banks to news. Both bank-specific and common market-level news (such as macroeconomic announcements) can induce jumps in individual stocks. Our sample represents the largest banks in the euro area, thus the return of a portfolio of their stocks should only jump due to common market-level news, since idiosyncratic should be diversified away. This means that co-jumps occur across many stocks at the same time. Hence, besides analysing jumps in the individual bank stock returns, we also examine jumps in the aggregate portfolio, as in Bollerslev, Law and Tauchen (2008).

There is compelling empirical evidence in the finance literature[1] that asset prices are subject to occasional jumps, so the classical paradigm of continuous sample path can be discredited. The continuous-time jump-diffusion modelling of asset returns dates back to Merton (1976). However, the identification of realised jumps from an observed time series is not trivially available, thus the empirical treatment of jump-diffusion models has been a serious challenge for decades. Most applied work relies on computationally intensive numerical simulation-based methods (e.g., the EMM, simulated maximum likelihood method of Brandt and Santa-Clara, 2002, and Durham and Gallant, 2001; the calibration method of Bates, 1996 and 2000; and the implied-state GMM of Pan, 2002), although recent Bayesian MCMC techniques provide a powerful procedure that outperforms other methods (see Jacquier, Polson and Rossi, 1994; and Eraker, Johannes and Polson, 2003, among others).

The seminal work of Barndorff-Nielsen and Shephard (2004b, 2006) provides a non-parametric technique to identify realised jumps in high-frequency asset return series.[2] The method is based on a result of recent literature (see Andersen, Bollerslev, Diebold and Labys, 2003; and Barndorff-Nielsen and Shephard, 2004a, among others) that states that the sum of squared intraday returns provides a consistent estimate of the true volatility of the underlying continuous-time process. Barndorff-Nielsen and Shephard (2004b) showed that the quadratic variation of returns can be split up into a diffusive and a jump component, and that these two components can be estimated

[1] See Andersen and Lund (1997), Johannes (2004), Huang and Tauchen (2005) and Andersen, Bollerslev and Diebold (2007), among others.

[2] Alternative jump detection methods have been proposed in the literature, and include Jiang and Oomen (2005) which is based on swap variance contracts, and Christensen and Podolski (2006) which relies on range statistics.

separately by using the so-called realised bipower variation. The advantages of this method are that it does not require the estimation of the drift and diffusion functions and that there is no need for a particular specification of the jump process. However, it has to be noted that the approach cannot be applied in situations where jump arrivals follow a Lévy process with infinite small jumps in a finite time period, but it is powerful when jumps arrive according to a compound Poisson process. The latter is more realistic, because empirically observable jumps are rare and large, and are likely to be associated with news arrivals.

We apply Barndorff-Nielsen and Shephard (2004b)'s approach to identify jumps in our intraday bank stock return series. Since it is a non-parametric test, we need not specify and estimate any particular model, but only compute the appropriate volatility measures and the test statistics. Regarding testing for co-jumps, we apply the test proposed by Bollerslev et al. (2008) which heavily relies on Barndorff-Nielsen and Shephard (2004b)'s method.

The rest of the paper proceeds as follows. Section 2 introduces the basic quadratic variation theory underlying the jump detection methodology, and it also presents the test statistic. Section 3 discusses the data we use in this paper. Before testing for jumps in the individual and portfolio series, Section 4 provides a preliminary statistical analysis of the data. Not only raw returns are examined, but also realised volatilities. Moreover, the statistical analysis is carried out both over the whole sample period as well as over the two subsamples: before and after the financial crisis. Section 5 presents and interprets the results of jump tests. Finally, Section 6 concludes.

2 The theory of quadratic variation

Our starting point is a continuous-time jump-diffusion process for the log-price of the asset, defined on a complete probability space $(\Omega, \mathcal{F}_t, \mathbb{P})$, where $\{\mathcal{F}_t\}_{t\in[0,T]}$ is a right-continuous filtration and $\mathbb{P}$ is the data generating measure. Then the log-price process evolves over time as

$$\mathrm{d}p\,(t) = \mu\,(t)\,\mathrm{d}t + \sigma\,(t)\,\mathrm{d}W\,(t) + \kappa\,(t)\,\mathrm{d}q\,(t) \tag{1}$$

where $p\,(t)$ is the log asset price under $\mathbb{P}$, $\mu\,(t)$ and $\sigma\,(t)$ are the $\mathcal{F}_t$-adapted instantaneous drift and volatility functions (possibly stochastic), $W\,(t)$ is a standard Brownian motion, $q\,(t)$ is a counting process, possibly a non-homogeneous Poisson process with time-varying intensity $\lambda\,(t)$, and $\kappa\,(t)$ is a predictable process, denoting the identically distributed (log) jump size, defined as $p\,(t) - p\,(t-)$. Its mean $\mu_\kappa\,(t)$ and standard deviation $\sigma_\kappa\,(t)$ are also $\mathcal{F}_t$-adapted processes. It is assumed that $W(t)$, $q(t)$ and $\kappa(t)$ are independent of each other. In the absence of jumps, the underlying process is an Itô process with continuous sample paths. Following Lee and Mykland (2008), assume that the drift and volatility processes do not change dramatically over short periods of time.

In practice, the price process can only be observed at discrete times. For simplicity, it is assumed that the sampling periods are equally spaced, i.e., for day t, the M price observations can be written as $p(t-1+\Delta), p(t-1+2\cdot\Delta), \ldots, p(t)$, where $\Delta \equiv 1/M$. Then, intra-daily returns are defined as

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

where $r_{t,j}$ denotes the jth within-day return on day t.

The *quadratic variation* process of $r_t \equiv p(t) - p(t-1)$, which represents the cumulative realised sample path variation of r_t, is given by

$$QV(t, t-1) = \int_{t-1}^{t} \sigma^2(\tau)\,\mathrm{d}\tau + \sum_{t-1\leq\tau\leq t} \kappa^2(\tau) \tag{3}$$

where the first term in the sum, $\int_{t-1}^{t} \sigma^2(\tau)\,\mathrm{d}\tau$, is the *integrated variance*, $IV(t, t-1)$, which provides the diffusive sample path variation over the interval $(t-1, t]$. In the absence of jumps, $QV(t, t-1) = IV(t, t-1)$.

Semi-martingale theory ensures that the *realised variance*, defined as

$$RV_t \equiv \sum_{j=1}^{M} r_{t,j}^2, \tag{4}$$

is a consistent estimator of the total quadratic variation, regardless of the presence of jumps, as $M \longrightarrow \infty$ (or $\Delta \longrightarrow 0$). That is, $\operatorname{plim} RV_t = QV(t, t-1)$.

It is obvious from equation (3) and the convergence result above that the realised variance will inherit the dynamics of both the continuous sample path component of the total QV (IV) and the jump component. As shown by Andersen, Bollerslev and Diebold (2006), the diffusive and jump volatility components have different persistence properties, particularly, whereas realised variances exhibit strong autocorrelation, the serial correlations of the jump components are much weaker. This suggests that it is desirable to get separate estimates of these two components for a more accurate volatility modelling and forecasting. Andersen et al. (2006) shows indeed that there are significant gains in terms of volatility forecast accuracy when differentiating the diffusive and jump components.

In order to split up the individual components of QV, Barndorff-Nielsen and Shephard (2004b) proposed the use of the so-called *realised bipower variation*, defined as

$$RBV_t \equiv \mu_1^{-2} \frac{M}{M-1} \sum_{j=2}^{M} |r_{t,j}| \, |r_{t,j-1}| \tag{5}$$

where $\mu_1 \equiv \mathbb{E}(|Z|) = \sqrt{2/\pi} \approx 0.7979$ with $Z \sim \mathcal{N}(0,1)$. Barndorff-Nielsen and Shephard (2004b) showed[3] that, under reasonable assumptions,

$$\operatorname{plim} RBV_t = IV \equiv \int_{t-1}^{t} \sigma^2(\tau)\, \mathrm{d}\tau \qquad \text{as } M \longrightarrow \infty. \tag{6}$$

Hence, the realised bipower variation consistently estimates the continuous sample path component of QV, even in the presence of jumps.

As a consequence, by combining this result with that of RV, a consistent estimator of the cumulative squared jump component can be obtained as

$$\operatorname{plim}(RV_t - RBV_t) = QV(t, t-1) - IV(t, t-1) = \sum_{t-1 \leq \tau \leq t} \kappa^2(\tau). \tag{7}$$

Building on these results, various jump statistics have been constructed to test for the presence of jumps in asset return series, see Barndorff-Nielsen and Shephard (2004b), Andersen et al. (2006) and Huang and Tauchen (2005). The extensive simulation results of Huang and Tauchen (2005) suggest that the ratio statistic,

$$RJ_t \equiv \frac{RV_t - RBV_t}{RV_t}, \tag{8}$$

has reasonable power against several stochastic volatility jump-diffusion models. Moreover, after appropriate scaling the distribution of the test statistic converges to the standard Gaussian. The scaled version of the jump statistic is

$$z_t = \frac{RJ_t}{\sqrt{\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right) \frac{1}{M} \max\left\{1, \frac{RTQ_t}{RBV_t^2}\right\}}}, \tag{9}$$

where $\mu_1^{-4} + 2\mu_1^{-2} - 5 = (\pi/2)^2 + \pi - 5 \approx 0.6090$, and RTQ_t refers to the *realised tripower quarticity*, defined by

$$RTQ_t \equiv \mu_{4/3}^{-3} \frac{M^2}{M-2} \sum_{j=3}^{M} |r_{t,j}|^{4/3} \, |r_{t,j-1}|^{4/3} \, |r_{t,j-2}|^{4/3}, \tag{10}$$

[3] Later Barndorff-Nielsen and Shephard (2006) and Barndorff-Nielsen, Graversen, Podolskij and Shephard (2005) provided weaker conditions for the convergence results.

and $\mu_{4/3} \equiv \mathbb{E}\left(|Z|^{4/3}\right) = 2^{2/3}\Gamma\left(7/6\right)/\Gamma\left(1/2\right) \approx 0.8309$. Barndorff-Nielsen and Shephard (2004b) showed that plim $RTQ_t = IQ\left(t, t-1\right) \equiv \int_{t-1}^{t} \sigma^4\left(\tau\right) \mathrm{d}\tau$ as $M \longrightarrow \infty$, where IQ is the *integrated quarticity*. Note that other consistent estimators of IQ based on the summation of adjacent returns raised to powers less than two where the powers sum to four also serve, see Barndorff-Nielsen and Shephard (2004b).

3 Data description

Our dataset consists of tick-by-tick transaction prices of 17 big euro area bank stocks, traded in four exchanges: Bolsa de Madrid (the Spanish stock exchange), Borsa Italiana (the Italian stock exchange), Deutsche Börse (the German stock exchange), and Euronext which is the most liquid exchange group in the world which brings together six cash equities exchanges in seven countries. Our sample contains stock prices traded by Euronext from three countries: Belgium, France and Portugal. The data was purchased from Tickdata, one of the biggest providers of high-frequency data, and kindly provided by the European Central Bank (ECB). For a list of banks in our dataset and for additional information, see Table 1.

Our sample of banks is quite heterogeneous in terms of how they were affected by the recent financial crisis. There are "healthy" banks, which have not suffered huge losses during the crisis, indeed, for example, Banco Santander has become the largest bank in Europe in terms of market capitalisation. On the other hand, some of the banks in the sample needed government help to survive the crisis. Unicredit had serious financial troubles in 2008 and turned to the Italian government for help. As a consequence, the bank did not pay cash dividend in 2008. Hypo Real Estate was announced to get a credit line of €35 billion from the German government and a consortium of German banks in September 2008 owing to its financial problems. Dexia was bailed out by the Belgian, French and Luxembourg governments on September 30, 2008 by €6.4 billion, while Fortis was bought by the Dutch and Belgian governments in October 2008. Société Générale has come into limelight by announcing on January 24, 2008 that one of its futures traders had committed a fraud of almost €5 billion, the largest in history. Another French bank, Natixis, was also strongly hit by the financial crisis, and in less than two years it lost about 95% of its value. Finally, Crédite Agricole is the French bank which was the mostly affected by the financial crisis due to its big losses in the CDO market.

In addition to the financial crisis, the time series of two banks' stock prices were also affected by other issues. In July 2007 Bankinter decided on a stock split at the ratio of 1 : 5, so that the stock price was adjusted on July 23, 2007, inducing a drop from about 60 to 12. This is evidently not a jump, but just a new price for the bank's stocks. Since we are working with returns, only the return in the time interval of this adjustment is impacted, thus this abnormal return is excluded from the series. Likewise, Natixis was created through the combination of the corporate and investment banking ans services activities of the Banque Populaire and Caisse d'Espargne groups in November 2006. Hence, after November 20, 2006 the share price of Natixis is used, while before this date we use the stock price of Banque Populaire. Again, the return on the time interval of the change is excluded from the sample.

The sample period varies with each bank, but even the shortest sample starts in January 2005, and all end on December 31, 2008. Hence, for each bank at least 4 years of intraday data is available, and we have sufficient data before and after the recent financial started in the summer of 2007.

The trading hours (see last column in Table 1) are almost the same for all the four exchanges, particularly, stocks are traded from 09:00 to 17:30 Central European Time (CET), with the exception of Borsa Italiana whose trading period is from 09:05 to 17:25. On each exchange there are opening and closing auctions which last 5–10 minutes before and after the continuous trading period, respectively. The main purpose of these auctions is to aggregate liquidity, and large institutional investors take advantage of this, so they are the main participants of the auctions. However, conversations with market participants suggest that closing auction prices may deviate from the rest of the trading day due to derivatives hedges carried out at the close of the market. For these reasons only transaction prices from the continuous trading period are used in this paper.

4 Data and descriptive analysis

From the tick-by-tick transaction prices time series of equally spaced observations are constructed.[4] This is done by using the previous tick method from Dacorogna, Gençay, Müller, Olsen and Pictet (2001), that is, for each time stamp the last observation of the time interval prior to the time stamp is taken. If in some time interval there is no observation the last observed price is used.

As sampling frequency, 5-minute intervals are chosen. They are the most widely used in the

[4] This only simplifies the work, and the whole analysis could also be carried out by using irregularly spaced price data.

empirical literature, since the frequency is high enough to obtain accurate volatility estimates and, on the other hand, the microstructure error, present at very high frequencies, is not as big as to distort the calculations.

Trading frequency (the number of ticks) increased considerably over the sample period, although the stocks of very large banks were also heavily traded at the beginning of the sample. This implies that these intraday prices are highly reliable. Moreover, since Tickdata provides clean, ready-to-use intraday time series, no cleaning has been necessary before constructing the 5-minute series. We exclude trades outside the continuous trading period as well as market holidays. In the Euronext exchanges there are some days a year with trading only until 14:00 CET, mainly around Christmas time, thus for those days the trading period is set from 09:00 to 14:00 CET.

4.1 Analysis of raw log returns

From the 5-minute prices log returns are calculated, as in equation (2). Descriptive statistics of the log returns are presented in Table 2.

4.2 Analysis of realised volatility

5 Jumps and co-jumps

6 Conclusion

Tables

Table 1: Data description

Exchange	Bank id	Country	Symbol	Bank name	Sample period	Trading hours
Bolsa de Madrid	23	ESP	BBVA	BBVA	3/1/2005–31/12/2008	09:00–17:30
	27	ESP	BKT	Bankinter	3/1/2005–31/12/2008	09:00–17:30
	107	ESP	SAN	Banco Santander	3/1/2005–31/12/2008	09:00–17:30
Borsa Italiana	48	ITA	ISP	Intesa Sanpaolo	2/1/2004–31/12/2008	09:05–17:25
	359	ITA	UCG	Unicredit	2/1/2004–31/12/2008	09:05–17:25
Deutsche Börse	73	GER	DBK	Deutsche Bank	2/1/2003–31/12/2008	09:00–17:30
	717	GER	CBK	Commerzbank	2/1/2003–31/12/2008	09:00–17:30
	808	GER	HRX	Hype Real Estate	7/10/2003–31/12/2008	09:00–17:30
Euronext	3183	BEL	KBC	KBC	2/1/2003–31/12/2008	09:00–17:30
	5216	FRA	BQP	Natixis Banque Popular	2/1/2003–31/12/2008	09:00–17:30
	29544	PRT	BES	Banco Espírito Santo	2/1/2004–31/12/2008	09:00–17:30
	29547	PRT	BCP	Banco Comercial Português	2/1/2004–31/12/2008	09:00–17:30
	9000005	BEL	DEX	Dexia	2/1/2003–31/12/2008	09:00–17:30
	9000006	BEL	FOR	Fortis	2/1/2003–31/12/2008	09:00–17:30
	9000022	FRA	CRA	Crédit Agricole	2/1/2003–31/12/2008	09:00–17:30
	9000052	FRA	SOC	Société Générale	2/1/2003–31/12/2008	09:00–17:30
	9000053	FRA	BNP	BNP Paribas	2/1/2003–31/12/2008	09:00–17:30

Table 2: Descriptive statistics of log 5-minute returns

	Bolsa de Madrid			Borsa Italiana		Deutsche Börse		
	23–BBVA	27–BKT	107–SAN	48–ISP	359–UCG	73–DBK	717–CBK	808–HRX
Mean	-4×10^{-6}	-2×10^{-6}	-3×10^{-6}	-2×10^{-6}	-7×10^{-6}	-3×10^{-6}	-1×10^{-6}	-1×10^{-5}
Std	0.0019	0.0026	0.0021	0.0023	0.0024	0.0026	0.0032	0.0049
Min	−0.0576	−0.0982	−0.0882	−0.0716	−0.1485	−0.0846	−0.1981	−0.8139
Max	0.1177	0.1421	0.1178	0.0866	0.0973	0.2553	0.2049	0.3110
Skew	4.2509	2.5343	1.3088	0.2198	−1.6423	8.6304	4.3359	−45.8408
Kurt	316.3	212.5	304.7	142.1	352.3	846.4	461.9	7866.5
T	104647	104646	104647	128269	128168	157383	157383	137298

	Euronext								
	3183–KBC	5216–BQP	29544–BES	29547–BCP	9000005–DEX	90000006–FOR	9000022–CRA	9000052–SOC	9000053–BNP
Mean	-2×10^{-6}	-1×10^{-5}	-5×10^{-6}	-6×10^{-6}	-8×10^{-6}	-2×10^{-5}	-4×10^{-6}	-3×10^{-6}	-2×10^{-6}
Std	0.0026	0.0038	0.0019	0.0031	0.0029	0.0040	0.0026	0.0027	0.0024
Min	−0.2034	−0.4930	−0.2579	−0.0996	−0.1119	−0.9969	−0.0875	−0.0880	−0.0744
Max	0.1821	0.2025	0.0700	0.1349	0.2037	0.1423	0.1953	0.1486	0.0960
Skew	−1.6268	−12.8538	−16.5595	0.6270	4.8436	−94.9296	3.6451	2.6506	0.6420
Kurt	815.8	1992.7	2402.6	62.6	474.3	23508.3	371.8	242.3	132.6
T	157852	157645	131278	131690	157852	157028	157749	155586	157852