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CONDITIONAL JUMPS IN VOLATILITY AND THEIR ECONOMIC DETERMINANTS

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Conditional jumps in volatility and their economic determinants *

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Abstract

The volatility of financial returns is affected by rapid and large increments. Such movements can be hardly generated by a pure diffusive process for stochastic volatility. On the contrary jumps in volatility are important because they allow for rapid increases, like those observed during stock market crashes. We propose an extension of HAR model for estimating the presence of jumps in volatility, using the realized-range measure as a volatility proxy. By focusing on a set of 36 NYSE stocks, we show that, once that squared jumps in prices are disentangled from integrated variance, then there is a positive probability of jumps in volatility, conditional on the past information set. We then focus on the contribution of jumps during periods of financial turmoil. We analyze the dependence between the first principal component of the volatility jumps with a set of financial covariates including VIX, S&P500 volume, CDS, and Federal Fund rates. We observe that CDS captures large part of the expected jumps moves, verifying the common interpretation that large and sudden increases in volatility in stock markets over some days in the recent financial crisis have been caused by credit deterioration of US bank sector. Finally, we extend the model incorporating the credit-default swap in the dynamics of the jump size and intensity. The estimates confirm the significant contribution of the credit-default swap to the dynamics of the volatility jump size.

Keywords: Volatility, Jumps in volatility, Realized range, HAR.

J.E.L. codes: C22, C58, G10

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1 Introduction

Recent empirical studies indicate that diffusive stochastic volatility and jumps in returns are incapable of capturing the empirical features of equity index returns. Eraker et al. (2003) report convincing evidence that volatility of financial returns is affected by rapid and large increments. Such movements can be hardly generated by a pure diffusive process for stochastic volatility. More precisely, in a pure diffusive stochastic volatility setup, volatility can only increase by a sequence of small positive increments. On the contrary jumps in volatility are important because they allow for rapid increases, like those observed during stock market crashes. Eraker et al. (2003) results strongly suggest the presence of both jumps in volatility and returns. They also note that jumps in returns can generate large returns but the impact of jumps is transient. Furthermore, diffusive stochastic volatility and jumps in returns can both generate realistic patterns of both unconditional and conditional non-normalities in returns, but they have difficulties in capturing the pattern followed by conditional volatility of returns. Differently, jumps in volatility are rapid but persistent factors driving volatility. In fact, once at the high level, volatility reverts to its long run mean, so that jumps in volatility have a persistent effect. In those cases, the Broadie et al. (2007) test to detect jumps in volatility rejects a square-root stochastic volatility model and an extension with jumps in prices. A reason might be that these models include volatility increments which are approximately normal. Differently, Broadie et al. (2007) show that a model with contemporaneous jumps in volatility and prices easily passes these tests. In Eraker et al. (2003), Eraker (2004), Broadie et al. (2007), and Chernov et al. (2003) the estimation of jumps in volatility is based on stochastic volatility models, with jumps in prices and/or in instantaneous volatility, expressed in continuous time. Todorov and Tauchen (2011), by means of a non-parametric analysis on the VIX volatility index, find that market volatility involves many small changes as well as occasional big moves, where the presence of big moves justifies the use of jumps in volatility modelling. Further, they find strong correlation between return and volatility jumps measured as realized jumps in both series. In general, both the return-based and option-based evidence support the presence of jumps in returns as well as jumps in volatility.

In continuous-time setting, adding jumps to stochastic volatility models involves an additional set of latent state variables. The estimation of stochastic volatility with jumps in returns and/or volatilities can be possible only if the unobserved state variables are filtered out. Chernov et al. (2003) use the EMM, Pan (2002) adopt the implied-state technique to fit her models to returns and option prices. Eraker et al. (2003), Eraker (2004), estimate by means of simulation-based methods. Li et al. (2008) employ MCMC techniques for inferences of continuous-time models with stochastic volatility and infinite-activity Lévy jumps using discretely sampled data.

We contribute to this strand of the financial econometrics literature by focusing on the modeling and on the estimation of the jump component in volatility in discrete time. As a distinctive feature of our contribution, we use realized ranges as non parametric ex-post measure of the daily integrated volatility. Such a choice allows simplifying the computational burden of estimating the jumps in volatility as it circumvents the need to integrate out unobservable quantities. As Todorov (2009, 2011) has pointed out, the convenience of this method stems from the fact that the inference on the volatility process is based on estimates of latent quantities of the price process, i.e. the integrated volatility and the sum of squared jumps. For example, we can make inference on the volatility jumps regardless of how complicated the model for the stochastic volatility is. Furthermore, recent theoretical findings by Christensen and Podolskij (2007), prove that realized range, that is based on prices sampled at intradaily frequency, is a very efficient estimator of the quadratic variation of the returns. In our framework, efficiency of the integrated variance estimation is a crucial element, since the potential reduction of the measurement error obtained with realized-range measures can lead to more precise evaluations of the volatility jump component. Given that our focus is on the volatility jumps, we employ the so called bias corrected range-based bipower variation, see Christensen et al. (2009). This is a consistent estimator of the integrated variance, when the price process is affected by jumps and contaminated by microstructure noise. In this way, we are able to disentangle the jump component due to the presence of jumps in prices from the total price variation, leaving us with a volatility series that contains the volatility jumps, and allow us to identify them, if present. Consequently, we treat the bias corrected range-based bipower variation as its asymptotic limit, namely the integrated variance.

We thus propose a parametric model in discrete time to evaluate the probability and the intensity of the volatility jumps. In particular, given the well documented long-range dependence of the realized variance estimators, see Andersen et al. (2003) among others, and the persistent effects of jumps in volatility, we suggest a conditional model that generalizes the well known HAR model, introduced by Corsi (2009), but anticipated in meteorological applications by Jewson and Caballero (2003) with the AROMA model, allowing for the presence of an additive dynamic conditional volatility jump term. The jump component is modelled like a compound Poisson process allowing for multiple jumps per day, as in Chan and Maheu (2002) and Maheu and McCurdy (2004), whose intensity and magnitude parameters are varying over time according to an autoregressive specification. Following this approach, we are able to model and identify periods with an increasing volatility jump activity, that reflect periods of high market stress, since the unexpected jump risk cannot be hedged away and investors may demand a large risk premium to carry these risks. The discrete time specification of the HAR with a jump component, called Heterogeneous Autoregressive-Volatility-Jumps (HAR-V-J) model, is estimated by maximum likelihood.

The empirical analysis focus on 36 stocks quoted at the New York Stock Exchange, representing nine sectors of the U.S. economy: banks, insurance and financial services, oil gas and basic materials, food beverage and leisure, health care, industrial goods, retail and telecommunications, services, and technology. The estimation results point out that the jump activity is characterized by two different periods. The first one, from 2004 to 2007, of low jump activity, the second, from mid-2008 to mid-2009, of high jump activity. In particular, during the second period the jump component represents a relevant part of the estimated conditional volatility.

Given the estimated volatility jump sequences, we make a step forward toward the economic interdependence between them and some covariates. Rangel (2011) conducts a similar analysis focusing on the effect that scheduled announcements, like disclosure of public information regarding fundamental macroeconomic variables, have on the conditional jump intensity of daily market returns. Our idea is to verify if the conditional expected volatility jump components estimated for the set of stocks considered share some common components. The principal components analysis (PCA) suggests that there is a jump volatility factor that is able to resume most of the observed variability in the conditional expected jumps. We relate this jump volatility factor to a set of daily financial variables, such as VIX, trading volume of S&P 500, Federal Funds rate, and credit default swaps (CDS) on the US banks in order to investigate the potential determinants of occasional big moves in asset's volatility. The main result of empirical analysis is that CDS capture large part of the expected jumps moves, verifying the common interpretation that large and sudden increases in volatility in stock markets over some days in the recent financial crisis have been caused by credit deterioration of US bank sector. We also argue that this result is not driven by the inclusion of the financial sector in the analysis. In fact, a robustness check made excluding the volatility jumps associated with banks, lead to almost identical results.

This paper is organized as follows. In Section 2 the econometric model is set out and the estimation procedure is outlined. Section 3 illustrates the estimation results of the HAR-V-J model with data on 16 NYSE stocks. Section 4 investigates the determinants of the common component of estimated expected jumps and presents the estimates of an extended version of the HAR-V-J. Section 5 concludes. The Appendix summarizes some results associated with the realized range and presents the realized range estimator and the bias-corrected realized range-based bipower variation which are used in the empirical analyses.

2 A model for realized range volatility with jumps

Our first research question is associated with the estimation of the jumps contribution to the integrated volatility. A wide empirical literature is focused on modeling daily realized volatility. Andersen and Bollerslev (1998), Andersen et al. (2001) and Andersen et al. (2003), report evidence of long memory in the ex-post volatility measurements, as realized volatility. However, Lieberman and Phillips (2008) argue that the long memory found in realized volatility can be an artifact due to aggregation of intradaily squared returns. On the other hand, part of the literature, following Granger and Hyung (2004), connects the observed high persistence to the presence of level shifts in the mean of the volatility process, given that level shifts can generate spurious evidence of long memory, see also Christensen and Santucci de Magistris (2010) and Bordignon and Raggi (2010). The Heterogeneous Autoregressive (HAR) model by Corsi (2009), an extension of the HARCH model of Muller et al. (1997), approximates the long memory feature of ex-post volatility measures by means of a long lagged AR process.[1] The

[1]In this regard, see also McAleer and Medeiros (2008) and Martens et al. (2009) for an application in terms of forecast performance of a level shift model with HAR dynamics for realized volatility.

HAR model mimics the asymmetric propagation of volatility, due to the presence of heterogeneous market participants. It's an additive cascade model of different volatility components each of which is generated by the actions of different types of market players. This additive volatility cascade generates a simple long lagged AR-type model, as it considers averages of realized volatilities over different time horizons. In the most common HAR specification, the actual realized volatility is regressed on its past daily, weekly and monthly averages. The main advantage of the HAR is therefore represented by its estimation simplicity, given that the model can be evaluated by standard OLS.

Our research approach differs from the previously cited papers in the integrated volatility estimators adopted, as we already anticipated. In fact, we focus on the Realized Range and not on Realized Volatility. The Appendix discusses the estimator we consider, the bias-corrected realized range-based bipower variation, denoted as $RBV^{\Delta}_{m,BC}$. Such a quantity, which is a proxy of the integrated variance, is evaluated at the daily level from stock prices sampled at 1 minute intervals.

Here we focus on the extension of the model proposed by Corsi (2009), adding a conditional volatility jump component to the conditional mean. This additional term allows estimating the probability and the impact of the volatility jumps on the dynamics of the continuous part of the realized range, once it has been disentangled from the price jumps part (see the Appendix for details on the estimator). Let $X_t = \log RBV^{\Delta}_{m,BC,t}$ be the daily logarithm of bias-corrected realized range-based bipower variation and I^{t-1} be the time $t-1$ information set, the HAR-Volatility Jump (HAR-V-J) model for X_t is given by,

$$X_t = \mu + \phi_D X_{t-1} + \phi_W X^W_{t-1} + \phi_M X^M_{t-1} + Z_t + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2_\epsilon) \tag{1}$$

where

$$X^W_t = \frac{1}{5}\sum_{j=0}^{4} X_{t-j}, \quad \text{and} \quad X^M_t = \frac{1}{22}\sum_{j=0}^{21} X_{t-j}$$

represent the weekly and monthly volatility components, respectively, see also Corsi (2009). This model for X_t implies that the $RBV^{\Delta}_{m,BC}$ is given by a multiplicative structure such as

$$RBV^{\Delta}_{m,BC,t} = \exp\{\bar{X}_{t-1}\}\exp\{Z_t\}\exp\{\epsilon_t\}$$

where $\bar{X}_{t-1} = \mu + \phi_D X_{t-1} + \phi_W X^W_{t-1} + \phi_M X^M_{t-1}$. Hence, the jump term $J_t = \exp\{Z_t\}$ acts as a multiplicative factor in the volatility process. In case of no jumps $J_t = 1$, and the volatility follows a HAR process. The jump term, Z_t, in the period t log-volatility is given by

$$Z_t = \sum_{k=1}^{N_{\sigma,t}} Y_{t,k}$$

where the jump size is

$$Y_{t,k} \sim i.i.d.N\left(\Theta_{\sigma,t}, \Delta_{\sigma,t}\right).$$

ϵ_t and $Y_{t,k}$ are assumed to be independent. Following Chan and Maheu (2002), $\Theta_{\sigma,t}$ and $\Delta_{\sigma,t}$ are modelled as a function of past log-volatility, namely

$$\Theta_{\sigma,t} = \zeta_0 + \zeta_1 X_{t-1} \tag{2}$$

and

$$\Delta_{\sigma,t} = \eta_0 + \eta_1 X^2_{t-1}. \tag{3}$$

The jump component has a compound Poisson structure where the number of jumps arriving between $t-1$ and t, $N_{\sigma,t}$, is a Poisson counting process with intensity parameter $\Lambda_{\sigma,t} > 0$ and density

$$P\left(N_{\sigma,t} = j | I^{t-1}\right) = \frac{e^{-\Lambda_{\sigma,t}} \Lambda^j_{\sigma,t}}{j!}, \qquad j = 0, 1, 2, ...$$

This implies that

$$\mathrm{E}\left[N_{\sigma,t} | I^{t-1}\right] = \mathrm{Var}\left[N_{\sigma,t} | I^{t-1}\right] = \Lambda_{\sigma,t}$$

so that the conditional density of Z_t given $N_{\sigma,t}$ and I^{t-1} is

$$Z_t | N_{\sigma,t} = j, I^{t-1} \sim N\left(j\Theta_{\sigma,t}, j\Delta_{\sigma,t}\right) \tag{4}$$

Since $\mathrm{E}\left[Z_t | N_{\sigma,t} = j, I^{t-1}\right] = j\Theta_{\sigma,t}$, the conditional expected value of the jump component is

$$\mathrm{E}\left[Z_t | I^{t-1}\right] = \Theta_{\sigma,t}\Lambda_{\sigma,t} \tag{5}$$

where $\Theta_{\sigma,t}$ is assumed to be measurable with respect to I^{t-1}, as in (2). Given the conditional density of Z_t in (4), the conditional variance of the jump component is

$$\mathrm{Var}\left[Z_t|I^{t-1}\right] = \left(\Delta_{\sigma,t} + \Theta^2_{\sigma,t}\right)\Lambda_{\sigma,t}, \tag{6}$$

where $\Delta_{\sigma,t}$ is assumed to be measurable with respect to I^{t-1}, see (3). Whereas, as in Chan and Maheu (2002), the unobserved log-volatility jump intensity is assumed to follow an autoregressive conditional jump intensity specification

$$\Lambda_{\sigma,t} = \Lambda_0 + \lambda_1 \Lambda_{\sigma,t-1} + \psi \xi_{t-1} \tag{7}$$

such that the conditional jump intensity in period t depends on its own lag and on the lag of the innovation term ξ_t, which represents the measurable shock constructed ex-post by the econometrician. This shock, or jump intensity residual, is defined as

$$\xi_t = \mathrm{E}\left[N_{\sigma,t}|I^t\right] - \Lambda_{\sigma,t}.$$

thus ξ_t depends on the expected number of jumps measured with respect to the information set including the contemporaneous information, i.e. at time t. It follows that the jump intensity equation can be therefore rewritten as

$$\Lambda_{\sigma,t} = \Lambda_0 + (\lambda_1 - \psi)\Lambda_{\sigma,t-1} + \psi\,\mathrm{E}\left[N_{\sigma,t-1}|I^{t-1}\right]$$

with

$$\mathrm{E}\left[N_{\sigma,t}|I^t\right] = \sum_{j=0}^{\infty} j P\left(N_{\sigma,t} = j|I^t\right). \tag{8}$$

As noted by Chan and Maheu (2002) other functional forms that include nonlinearity also may be very useful. The filtered probabilities $P\left(N_{\sigma,t} = j|I^t\right)$ are obtained by means of the Bayes' law

$$P\left(N_{\sigma,t} = j|I^t\right) = \frac{P\left(X_t|N_{\sigma,t} = j, I^{t-1}\right)P\left(N_{\sigma,t} = j|I^{t-1}\right)}{P\left(X_t|I^{t-1}\right)}, \quad j = 0, 1, 2, \ldots \tag{9}$$

where

$$P\left(X_t|I^{t-1}\right) = \sum_{j=0}^{\infty} P\left(X_t|N_{\sigma,t} = j, I^{t-1}\right) P\left(N_{\sigma,t} = j|I^{t-1}\right)$$

and $P\left(X_t|N_{\sigma,t} = j, I^{t-1}\right)$ is given by the density of ϵ_t. Analogously, we can compute the conditional probability of tail events, such as $P(X_t > u|I^{t-1})$. This allows to compare the predictive abilities of events like log-volatility is above a given threshold of the HAR-V-J model to the Gaussian HAR model.

2.1 Log-likelihood

Given equation (4), the first two conditional moments of X_t are given by

$$\mathrm{E}\left[X_t|N_{\sigma,t} = j, I^{t-1}\right] = \mu + \phi_D X_{t-1} + \phi_W X_{t-1}^W + \phi_M X_{t-1}^M + j\Theta_{\sigma,t}$$

and

$$\mathrm{Var}\left[X_t|N_{\sigma,t} = j, I^{t-1}\right] = \sigma_\epsilon^2 + j\Delta_{\sigma,t}.$$

As in Chan and Maheu (2002) the likelihood function of the model, conditional on the number of arrivals,$N_{\sigma,t} = j$, and to I^{t-1}, is therefore given by

$$f(X_t|N_{\sigma,t} = j, I^{t-1}) = \frac{1}{\sqrt{2\pi(\sigma_\epsilon^2 + j\Delta_{\sigma,t})}} \exp\left(-\frac{(X_t - \mu - \phi_D X_{t-1} - \phi_W X_{t-1}^W - \phi_M X_{t-1}^M - j\Theta_{\sigma,t})^2}{2(\sigma_\epsilon^2 + j\Delta_{\sigma,t})}\right)$$

so that the log likelihood function conditional on I^{t-1} is given by

$$\ell(X_t|I^{t-1}) = \log\left(\sum_{j=0}^{\infty} P(N_{\sigma,t} = j|I^{t-1}) \cdot f(X_t|N_{\sigma,t} = j, I^{t-1})\right) \tag{10}$$

The likelihood function is then maximized with respect to the parameter vector, $\theta = \{\mu, \phi_D, \phi_W, \phi_M, \zeta_0, \zeta_1, \eta_0, \eta_1, \lambda_0, \lambda_1, \psi, \sigma_\epsilon^2\}$. In the computation of the log-likelihood function the expression in (10) is approximated by a finite sum, where we employ a truncation value of 20.

Adopting the expression in Maheu and McCurdy (2004, p.766), the first four conditional moments of X_t are:

$$\mathrm{E}[X_t|I^{t-1}] = \bar{X}_{t-1} + \Lambda_{\sigma,t}\Theta_{\sigma,t} \tag{11}$$

$$\mathrm{Var}[X_t|I^{t-1}] = \sigma_\epsilon^2 + \Big(\Theta_{\sigma,t}^2 + \Delta_{\sigma,t}\Big)\Lambda_{\sigma,t} \tag{12}$$

$$\mathrm{Sk}[X_t|I^{t-1}] = \frac{\Lambda_{\sigma,t}\Big(\Theta_{\sigma,t}^3 + 3\Theta_{\sigma,t}\Delta_{\sigma,t}\Big)}{\Big[\sigma_\epsilon^2 + \Big(\Theta_{\sigma,t}^2 + \Delta_{\sigma,t}\Big)\Lambda_{\sigma,t}\Big]^{3/2}} \tag{13}$$

$$\mathrm{Kur}[X_t|I^{t-1}] = 3 + \frac{\Lambda_{\sigma,t}\Big(\Theta_{\sigma,t}^4 + 6\Theta_{\sigma,t}^2\Delta_{\sigma,t} + 3\Delta_{\sigma,t}^2\Big)}{\Big[\sigma_\epsilon^2 + \Big(\Theta_{\sigma,t}^2 + \Delta_{\sigma,t}\Big)\Lambda_{\sigma,t}\Big]^{2}} \tag{14}$$

The expected value of $RBV_{m,BC,t}^{\Delta} = \exp\{X_t\}$ conditional on I^{t-1} is

$$E\big[RBV_{m,BC,t}^{\Delta}|I^{t-1}\big] = \sum_{j=0}^{\infty}\Bigg[P\left(N_{\sigma,t} = j|I^{t-1}\right)\cdot\exp\left\{\bar{X}_{t-1} + j\Theta_{\sigma,t} + \frac{1}{2}(\sigma_\epsilon^2 + j\Delta_{\sigma,t})\right\}\Bigg] \tag{15}$$

Finally, the conditional expectation of $J_t \equiv \exp\{Z_t\}$ is given by

$$J_{t|t-1} \equiv E\big[J_t|I^{t-1}\big] = \sum_{j=0}^{\infty} P\big(N_{\sigma,t} = j|I^{t-1}\big)\cdot\exp\Big(j\Theta_{\sigma,t} + \frac{1}{2}j\Delta_{\sigma,t}\Big). \tag{16}$$

In the next section, we estimate the HAR-V-J model by ML, following the steps outlined above, to disentangle the volatility jump component, J_t, from the continuous volatility term, represented by $\bar{X}_{t-1}$.

3 Volatility jumps in the US market

Our analysis is based on the intradaily returns of 36 equities of the S&P 500 index. Prices are sampled at one minute frequency, from January 2, 2004 to December 31, 2009, for a total of 1510 trading days. The companies considered are shown in Table 1. We compute the $RBV_{m,BC,t}^{\Delta}$, for each stock, according to (24), using one-minute returns. The parameter m is set equal the average number of returns in one minute interval in each trading day for each stock considered, while the number of intradily ranges is $n = 390$.

Figure 1 plots the dynamic behavior of the volatility of BA, IBM, JPM, and UPS. The volatility is characterized by two dominant regimes. A long period of low volatility, approximately from 2004 to 2007, which is followed by a period of high volatility in correspondence of the financial crisis. It is interesting to note that the first part of the sample is not characterized by large jumps, while the period in correspondence of the recent financial crisis has many large spikes. As expected, this suggests that during financial crises, the probability and the magnitude of the jumps are higher.

As it is apparent from the second and third columns of Table 3, the series are right-skewed and leptokurtic. The sample skewness is around 1, on average, while the kurtosis is generally higher than three but smaller than six. This positive skewness could be related to the presence of a few large values in the $\log RBV^{\Delta}_{m,BC,t}$ series, such as those observed during the financial crisis (2008-2009). The unconditional non-normality could stem from the presence of jumps in the volatilities, as well as to changes in the conditional behavior of the series. Explicitly accounting for the presence of jumps allows to assume the conditional normality of the shocks, as in (1). We estimate the model in (1) according to the maximum likelihood procedure outlined in previous section. Table 2 reports the estimated parameters of the HAR-V-J for the 36 stocks under analysis. Introducing the jump component in the model induces a better in-sample fit. The likelihood-ratio test strongly rejects the null hypothesis, i.e. the HAR model with no jumps, in all cases. Thus, when $\Lambda_{\sigma,t}$, $\Theta_{\sigma,t}$ and $\Delta_{\sigma,t}$ are allowed to vary over time, we obtain an improvement over the more traditional HAR model without jumps.

Focusing on the jump size mean, we note that the estimates of ζ_0 in (2) are significant in 18 out of 36 cases, while those of ζ_1 are generally positive but not statistically different from zero. Furthermore, in 17 cases the jump size is statistically not different from zero, namely the impact of jumps on the conditional mean of X_t tends to be centered around zero on average. However, this does not imply that jumps do not affect the conditional moments of log-volatility. Even when $\Theta_{\sigma,t} = 0$ the jump dynamics affects the first four conditional moments in (11)-(14), and thus the tail realizations. In particular, conditional skewness of log-volatility is affected by the magnitude and sign of $\Theta_{\sigma,t}$. The sample averages for the 36 stocks of $\mathrm{Sk}(X_t|I^{t-1})$, reported in Table 3 are always positive and smaller than one. This means that including the jumps in the model allows to partially account for the positive skewness observed in the log-volatility. Analogous considerations hold for the sample averages of the conditional kurtosis.

The estimated jump sizes of the four stocks, representative of different sectors, plotted in

Figure 2, display a similar behavior in the case of BA, IBM, and JPM. The average jump size increases as the level of volatility increases, such as during the last two years. This is particularly evident for the bank sector. On the contrary, when ζ_1 is close to 0, such as in the case of UPS the plot of the estimated jump size looks like a constant across time. We found a similar result for the parameters in the jump size variance, see (3). In fact, η_0 is generally significant and positive while η_1 is not statistically different from zero, so that the variance of the jumps sizes can be restricted to be constant.

Now, if we turn to the parameters of $\Lambda_{\sigma,t}$, the jump intensity, we have that the persistence parameter, λ_1, is strongly significant and close to 1 in most cases. It is noteworthy that the estimates are greater than 0.9 in 24 out of 36 cases. This result confirms the evidence in Eraker et al. (2003) and Duffie et al. (2000), where the jump arrivals in volatility are highly persistent, producing clusters in jumps.

The plots of the expected number of jumps in Figure 3 suggest the presence of three regimes in the jumps intensity. The first period, from 2004 to the beginning of 2007, is characterized by an absence of jumps in volatility (the number of jumps is on average one in twenty days). In the second period, the estimated jump arrivals sharply increase to a daily average of 0.5-0.6, while between mid-2008 and mid-2009, the average number of jump arrivals dramatically increases, reaching an average of approximately one jump per day. We obtain slightly different results for $\Lambda_{\sigma,t}$ of JPM which has a sharper increase at mid of 2007 and remains high till the second part of 2009. This could be the outcome of the financial crisis, which hit the bank sector more than others. This is a common characteristic of the estimated jump intensities of the financial stocks in the sample. Qualitatively, this result is similar to the finding in Andersen et al. (2007, p.714, Figure 3), which depicts an important temporal dependence in the jump arrivals and in the jump sizes.

The ex-post probability of a jump, shown for the four stocks in Figure 4, illustrates the persistence in the $\Lambda_{\sigma,t}$ estimates. This also means that in the crisis period (2008-2009) the ex-post probability of observing at least one log-volatility jump approaches one. This is also an evidence of jump clustering which, in fact, characterizes all the series in the sample. The higher estimated jump activity in the second part of the sample explains also the increase in the unconditional expected value of the $\Lambda_{\sigma,t}$ process, see Table 3. The sample averages of the estimated $\Lambda_{\sigma,t}$ turn out to be, in a few case, larger than one. We think that this could be induced by abnormal variations in the log-volatility, occurred during the financial crisis, which somewhat affect the estimate of the $\Lambda_{\sigma,t}$ process parameters. Moreover, the parameter ψ of the innovation term is always positive, and significant in more than half of considered stocks. As a consequence the unobserved past innovation has a positive and significant impact on the jump intensity.

Figure 5 reports the estimated expected exponential jumps, $\hat{J}_{t|t-1}$. In all cases, the expected exponential jumps increase during the period 2008-2009, that is, jumps in volatility constitute an important source of price variability. By looking at the volatility of JPM, the expected jump component increases already after 2007. The role of the jumps for IBM and BA is relevant in the period between mid-2008 and mid-2009, namely during the recent financial crisis. It is evident from Figure 2 the role played by the specification of the jump size dynamics. It is noteworthy that the estimated ζ_1 in the jump size equation for IBM is significantly positive and larger compared to the others stocks. This means that when there is a sharp increase in the past volatility this has a significant impact on the jump size of IBM which drives up the overall jump component. On the other hand, the estimated jump intensity (Figure 3) follows a pattern close to those observed for the others. A completely different picture is obtained with the $\hat{J}_{t|t-1}$ of UPS, which remains rather low and stable for the entire period.

It is also interesting to study the difference between the ex-ante and ex-post probabilities of jumps during a given day. This can be done in our setup, simply comparing $P(N_{\sigma,t} = j|I^{t-1})$ with $P(N_{\sigma,t} = j|I^{t})$, where the latter is obtained by the Bayes law in (9). In particular, the recent financial crisis peaked on October 10, 2008, when annualized volatility of the S&P 500 index reached a peak of 120%. As it is clear from Figure 6, the estimated ex-ante and ex-post probabilities on October 10, 2008 have different patterns. In particular, the ex-ante probabilities of more than 1 jump, calculated using $\Lambda_{\sigma,t}$, are already high and centered on 1-2 jumps. On the other hand, after the arrival of the information on the volatility for October 10, 2008, the ex-post jump probability distribution is shifted to the right, such that we have a higher probability of observing 3-4 jumps on that day. Finally, looking at the Ljung-Box test on the model residuals, see the last columns of Table 2, it is clear that for some series the HAR-V-J model is not able to completely capture the dynamics of the log-volatility series.

This is due to the peculiar autoregressive lag structure of the HAR-RV model which appears too restrictive for a many series under exam, thus leaving some autocorrelation in the residuals. Alternatively, adopting an ARFIMA model one could optimally select the lag structure such that the persistent component of volatility is accounted for. However, this is beyond the scope of the present paper, since the focus is on the modeling of the jump term. It is important to stress that the autocorrelation in the residuals is not due to the inclusion of the jump term in the HAR-V model.

In Table 3 we show the sample averages of conditional moments of the expected number of jumps, as computed in (8), and of conditional moments of X_t, as in (12)-(14). The average ex-post number of jumps is very close to the expected number of jumps, meaning that the specification of $\Lambda_{\sigma,t}$ correctly estimates the conditional mean of $E[N_{\sigma,t}|I^t]$. Since, the HAR-V-J model is a non-Gaussian conditional model for X_t due to the presence of jumps it generates positive skewness and mild leptokurtosis.

Table 3 also reports the sample correlations of the expected exponential jump component, $E[J_t|I^{t-1}]$ with the squared price jumps, defined as $\sum_{i=1}^{N_p(t)} \xi_i^2$ (see (23)). The jumps are estimated by $\Xi_t = \lambda_{2,m}\,(RRG_{BC} - RBV_{BC})$. The interesting finding is a positive correlation with the squared jumps-in-price component (see for an analogous result see Todorov and Tauchen, 2011). This finding confirms the evidence in Eraker et al. (2003) which suggest a positive association in the price and volatility jumps. In particular, this correlation is strengthened during the financial crisis, since the arrival of bad news induces not only jumps in prices, but also a sharp increase in the volatility. A possible explanation is that as traders receive new information, they revise their expectations, causing an increase in the disagreement on the fair price that leads to higher volatility.

In order to highlight the ability of the HAR-V-J model in predicting the log-volatility one-day ahead, we compute $P(RBV^{\Delta}_{m,BC,t} > u|I^{t-1})$, where u is the level of the annualized volatility. We choose October 10, 2005, as a day of low volatility, and October 10, 2008, as a day of extremely high volatility, with u equal to 30% for October 10, 2005, and to 120% for

October 10, 2008. This probability is given by

$$\Pr\left[RBV^{\Delta}_{m,BC,t} > u|I^{t-1}\right] = \sum_{j=0}^{\infty}\left[P\left(N_{\sigma,t} = j|I^{t-1}\right)\cdot\left(1-\Phi\left(\frac{u-\mu_t}{\sigma_t}\right)\right)\right]$$

where

$$\mu_t = E[X_{t-1}|N_t = j, I^{t-1}] = \bar{X}_{t-1} + j\Theta_{\sigma,t}$$

$$\sigma_t^2 = Var[X_{t-1}|N_t = j, I^{t-1}] = \sigma_\epsilon^2 + j\Delta_{\sigma,t}$$

where $\Phi(\cdot)$ is the standard Normal cdf. This simple exercise allows to evaluate how much the introduction of the jump component in the HAR increases the conditional probability of observing abnormal levels of volatility. The results in Table 4 clearly illustrates that the HAR-V-J behaves better than the Gaussian HAR for both threshold levels. This is not surprising because the positive conditional probability of observing more than one jump, as already seen above, dramatically increases the conditional probability that the log-volatility is above a given threshold, as shown in the case of $u = 120\%$. In general, the performances of the two models for October 10, 2005, are very similar, and a conditional probability equal to zero is given to the event of observing a volatility above 30%. It is interesting to note that the conditional probability that the annualized RBV is larger than 30% in October 10, 2005, for *Ford*, is correctly anticipated by the HAR-V-J while the estimated probability obtained with the Gaussian HAR is zero. A completely different picture is obtained in October 10, 2008, when the average level of volatility is much higher and the possibility of observing a level higher than 120% is much more likely. In this case, the HAR-V-J is able in the majority of the stocks considered to give a conditional probability of an extreme realization around 30% which is much higher than the probability implied by the Gaussian HAR.

4 Volatility jumps and financial covariates

Understanding the origins of jumps in returns and volatility is a topic of considerable interest to both theorist and market practitioners. In this section we focus on the economic determinants of volatility jumps. To this end, we investigate to what extent the estimated jump components in $\log RBV^{\Delta}_{m,BC,t}$ are driven by common factors. We aim at identify variables that have predictive power for the future occurrence of jumps for the stocks considered. We consider in our analysis financial and policy variables that are informative on the market expectations of the future economic activity and on the perceived risks of the financial system.

We regress the estimated exponential jump components, $\hat{J}_{t|t-1}$, of each stock on a set of lagged financial variables[2]: the first difference of the logarithm of S&P 500 volume, $\Delta\, Volumes$; the daily log-return of S&P, $\Delta S\&P$; the log-return of the DJ-UBS Commodity Index, $\Delta\, Commodity$; the first difference of the logarithm of the Federal Reserve trade-weighted US dollar index, $\Delta Exchange$; the first difference of the logarithm of the volatility index VIX, $\Delta\, VIX$; the excess yield on Moody's seasoned Baa corporate bond over the Moody's seasoned Aaa corporate bond, the credit spread or CS; the difference between the 10-Year and 3-months Treasury constant maturity rates, the term spread or TS; the difference between the effective and the target Federal Funds rates, FF; and the US Banks sector credit default swap index, CDS. The estimated parameters are shown in Table 5. From the results is evident that only the last three variables, namely TS, FF, and CDS, are significant for almost all the stocks. Moreover, it should be noted that the signs of the estimated coefficients are the same across the individual stocks. This suggests that there could be a common factor in the estimated jump components which can be predicted on the basis of lagged economic and financial variables.

To get further insights on the presence of a common factor in the individual jump components we extract the first principal component, PC_1, computed from the correlation matrix of the 36 estimated conditional jump series, $\hat{J}_{t|t-1}$. PC_1, explains approximately 63% of the overall variation (considering the first three components one arrives at 74%). The weights[3] in PC_1 are all positive with the exception of the loading of PFE, which is slightly negative. This could explained by the peculiar behavior of the estimated expected jump component of PFE which mostly depends on the value of ξ_{t-1} because the estimated λ_1 is very small (see Table 2). PC_1, plotted in Figure 7(a), is therefore a good proxy of the latent volatility jump factor. The dynamic pattern of PC_1 closely follows the behavior of the volatility series, and, as illustrated above, a sharp increase occurs in the levels of the expected volatility jumps during the financial crisis period. In order to investigate the determinants of the volatility jump series, we regress PC_1 on the same set of variables previously used. Table 6 reports the result of the

[2]We follow here the setup in Fernandes et al. (2009).
[3]Not reported to save space but available upon request from the authors.

regression. Expected jumps are significantly (and positively) correlated with the credit spreads and *CDS* (depicted in Figure 8), which reflect the perceived credit risk, especially during the financial crisis. The R^2 is higher than 37%, suggesting that *TS*, *CDS*, and *FF* have predictive power on jumps in volatility. Further, the partial r^2 reported in the last column, show that among the variables included in the regression only *FF* and *CDS* have nonzero correlation with the volatility jump factor. Jointly removing *TS*, *CDS*, and *FF* from the regression drastically reduces the R^2. Such a result might be driven by the inclusion in our sample of the financial sector. To address this issue, we extract the first principal component of the volatility jumps of 28 equities (thus excluding banks and insurance companies). The first PC explains again the 63% of the total variation and its pattern, shown in Figure 7(b), is almost indistinguishable from that of the entire set of assets. Furthermore, the second panel of Table 6 shows that the coefficient sign and magnitude are only slightly affected. The coefficient associated with the *CDS* maintain its significance, even if its magnitude is somewhat smaller. This might be explained by the direct effect that *CDS* have on the banks volatility. Analogous conclusions can be drawn looking at the partial r^2, which is still larger than 0.13 even when the financial sector is not included in the calculation of the principal components.

Given the predictive ability of *CDS* and the *FF* we extend the HAR-V-J model including both variables in the jump intensity and the expected jump size dynamic equations, as follows:

$$\Lambda_{\sigma,t} = \lambda_0 + \lambda_1 \Lambda_{\sigma,t-1} + \beta_1 CDS_{t-1} + \beta_2 |FF_{t-1}| + \psi \xi_{t-1} \tag{17}$$

$$\Theta_{\sigma,t} = \zeta_0 + \zeta_1 X_{t-1} + \zeta_2 CDS_{t-1} + \zeta_3 |FF_{t-1}| \tag{18}$$

where β_1 is restricted to be positive in order to guarantee that $\Lambda_{\sigma,t} > 0$[4]. However, from a simple analysis of the rolling estimates, shown in Figures 10(a)-10(d), calculated for the interval 21/12/2007 and 31/12/2009, it is evident that the estimates of β_2 and ζ_3 are highly unstable. The extent of this regime change during the crisis period clearly emerges also from Figure 9, which plots the dynamics of the absolute value of FF. This suggests the exclusion of FF_{t-1} from both equations, i.e. $\beta_2 = \zeta_3 = 0$. A completely different picture is obtained from the the rolling estimates[5] of β_1 and ζ_2, which turn out to be much more stable than those of β_2

[4] FF is in absolute value to guarantee the positivity of $\Lambda_{\sigma,t}$

[5] Available upon request from the authors.

and ζ_3, thus suggesting that the parameters can be consistently estimated, with the available sample, by maximum likelihood.

The estimation results are presented in Table 7, where emerges that *CDS* has a positive and significant effect on the size of the volatility jumps, but not on their intensity. Therefore, a worsening in the credit risk, as represented by the *CDS*, of financial intermediaries increases the expected size of the volatility jumps, and thus the market risk. These results confirm and extend those in Zhang et al. (2009) on the relation between credit risk, volatility risk and jumps. In particular, we stress that bad news on the default risk, that is an increase of the *CDS*, directly impacts on the expected size of the volatility jumps, causing a rapid variation in the price. The importance of the inclusion of the *CDS* in the jump equations is also shown by the improvement of the in-sample fit over the classic HAR model. In particular, Table 7 reports the Diebold-Mariano tests, which, in most cases is negative and often significant. Finally, in order to show the results of the HAR-V-J model with lagged CDS in the jump intensity and expected jump size dynamic equations and the differences with the model that does not include this variable, we calculate and plot in Figure 11 the ex-ante and ex-post probability of jumps on October 10, 2008. The estimated ex-ante and ex-post probabilities are markedly different from those obtained with the standard HAR-V-J (see Figure 6). In particular, the densities are less concentrated and assign larger probabilities to higher number of jumps. The differences between the probabilities in Figure 6 and those in Figure 11 can be explained by the introduction of the CDS in the model. Such a change is not confined to the pure interpretation of the estimated parameters but has effects involving the entire filtering approach leading to the identification of the jump component. As a result, and as expected, once the CDS is taken into account (through its introduction in the model), the probability of having a jump during the crisis are higher than those obtained without the CDS.

5 Concluding remarks

This paper studies the contribution of volatility jumps to the evolution of volatility. Differently from some earlier contribution we propose a modified version of the HAR for realized measure instead of relying on continuous-time stochastic volatility specification (as for example in Eraker et al., 2003, Broadie et al., 2007). We model the corrected bipower realized range, a consistent estimator of the integrated variance in presence of jumps in prices and microstructure noise, with a HAR-V-J model that allows for the presence of jumps in volatility. The inference on the parameters of the model is carried out using maximum likelihood estimation, after having specified the dynamics of the jumps sizes and intensities. The estimation results of the HAR-V-J model with high-frequency data from 36 stocks suggest that jumps in volatility are more likely to happen during the financial crises, i.e., when the level of volatility is high, and are positively correlated with jumps in prices. The second part of the analysis focuses on the common determinants of the jump component to the volatilities of individual stocks. It turns out that the variability of a common factor of the estimated jumps, obtained by principal components, can be predicted using a set of leading financial variables. In particular, CDS on US banks appears particularly significant in explaining the observed common jump component. This result reinforces the idea that the increase in volatility observed during the 2008-2009 US stock market turmoil has been provoked by the worsening of the credit risk of financial institutions. From this point of view the paper contributes to the understanding of the volatility evolution and in particular to the nature and the sources of volatility jumps. Finally, the HAR-V-J model is modified to incorporate the information content of CDS in the dynamics of the jump size and intensity. The estimation results of the extended HAR-V-J model confirm the significative contribution of the CDS to dynamics of the jump size, for all stocks considered.

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Appendix A: Realized range estimators

In this Appendix, we describe the integrated volatility estimator we adopt in our empirical study. Our objective is to estimate a suitable measure of the return variation over the trading day, that is disentangled from the jump in prices component.

Suppose first that the log-price of an asset, $p(t)$, follows a stochastic volatility model (SV):

$$p(t) = p(0) + \int_0^t \mu(u)\mathrm{d}u + \int_0^t \sigma(u)\mathrm{d}W(u), \quad t \geq 0 \tag{19}$$

where the mean process $\mu(t)$ is locally bounded and predictable, $\sigma(t)$ is assumed to be independent of Standard Brownian motion $W(\cdot)$ and càdlàg. Consider the equidistant partition $0 = t_0 < t_1 < \ldots < t_n = 1$ where $t_i = i/n$ and $\Delta = 1/n$ for $i = 1, \ldots, n$. If p is assumed to be fully observed, then the intraday range at sampling times t_{i-1} and t_i $(i = 1, 2, \ldots, n)$ would be computed as $s_{p,\Delta_i} = \max_{t_{i-1} \leq t,s \leq t_i} \{p_t - p_s\}$. However, to avoid biases associated with an infrequent trading activity (that might occur over a finite sample), we follow Christensen and Podolskij (2007) and assume that $mn+1$ equally spaced observations of the price are available, giving mn returns. Thus, there are n intervals each with m returns. The log-price for each time in the interval $(0, 1)$ is denoted as $p_{\frac{i-1}{n}+\frac{t}{mn}}$, where $i = 1 \ldots, n$ and $t = 0, \ldots, m$. The observed range over the i-th interval is given by $s_{p_i\Delta,\Delta,m} = \max_{0 \leq s,t \leq m} \left\{p_{\frac{i-1}{n}+\frac{t}{mn}} - p_{\frac{i-1}{n}+\frac{s}{mn}}\right\}$.

The RRG based on discrete observations is then

$$RRG_m^{\Delta} = \frac{1}{\lambda_{2,m}} \sum_{i=1}^{n} s^2_{p_i\Delta,\Delta,m}. \tag{20}$$

where $\lambda_{r,m} = E[s^r_{W,m}] = E\Big[\max_{0 \leq s,t \leq m} \left\{W_{t/m} - W_{s/m}\right\}^r\Big]$ is the r-th moment of the range of a standard Brownian motion over a unit interval when we observe only m increments of the underlying continuous time process. The value of $\lambda_{r,m}$ is obtained through numerical simulation of a standard Brownian motion observed m times over the unit interval and $\lambda_{2,m} \to \lambda_2 = 4\log(2)$ as $m \to \infty$. Moreover if we assume that the stochastic volatility process is of the kind in (19) and $m \to c \in \mathbb{N} \cup \infty$:

$$\frac{\sqrt{n}(RRG_m^{\Delta} - IV)}{\sqrt{\Lambda_m RRQ_m^{\Delta}}} \xrightarrow{d} N(0, 1)$$

with $\Lambda_m = \frac{\lambda_{4,m}-\lambda_{2,m}^2}{\lambda_{2,m}^2}$, and

$$RRQ_m^{\Delta} = \frac{n}{\lambda_{4,m}} \sum_{i=1}^{n} s_{p_{i\Delta},\Delta,m}^4.$$

The RRG_m^{Δ} is a consistent estimator of IV as $n \to \infty$, and is five times more efficient than realized volatility, see Martens and van Dijk (2007). In fact, RRG_m^{Δ} uses more information, both the maximum and minimum prices over a given interval, than the corresponding RV estimator, that takes into account just the last price of each interval Furthermore, Christensen and Podolskij (2007) show that, for very general continuous time processes for $\sigma(t)$, the Realized Range converges to the Integrated Volatility, $RRG^{\Delta} \xrightarrow{p} IV$. When the price is contaminated by microstructure noise, η_t, and the noise is modeled as an i.i.d. sequence of random variables with mean zero and finite variance ω^2, Christensen et al. (2009) show that the estimator of the integrated variance is

$$RRG_{m,BC}^{\Delta} = \frac{1}{\widetilde{\lambda}_{2,m}} \sum_{i=1}^{n} (s_{\widetilde{p}_{i\Delta},\Delta,m} - 2\widehat{\omega}_N)^2 \tag{21}$$

where

$$\widetilde{\lambda}_{r,m} = E\left[\left| \max_{t:\eta_{\frac{t}{m}}=\omega, s:\eta_{\frac{s}{m}}=-\omega} \left(W_{\frac{t}{m}} - W_{\frac{s}{m}}\right)\right|^r\right]. \tag{22}$$

The variance of the noise process ω^2 can be consistently estimated with $\widehat{\omega}_N^2 = \frac{RV^N}{2N}$, where RV^N is the realized variance computed using N intraday returns, with $N = nm$, i.e. the total number of log-returns, and $N^{1/2}\left(\widehat{\omega}_N^2 - \omega^2\right) \xrightarrow{d} \mathcal{N}(0, \omega^4)$.

If we consider, in addition to the microstructure noise, the presence of jumps in prices, that is the price follows a jump-diffusion process

$$p(t) = p(0) + \int_0^t \mu_1(u)\mathrm{d}u + \int_0^t \sigma(u)\mathrm{d}W_1(u) + \sum_{i=1}^{N_p(t)} \xi_i \tag{23}$$

where $N_p(t)$ counts the jumps arrivals at time t, and ξ_i is the jump size. Christensen et al. (2009) show that the bias-corrected realized range-based bipower variation, defined as:

$$RBV_{m,BC}^{\Delta} = \frac{1}{\widetilde{\lambda}_{1,m}^2} \sum_{i=1}^{n-1} |s_{p_{i\Delta},\Delta,m} - 2\widehat{\omega}_N||s_{p_{(i+1)\Delta},\Delta,m} - 2\widehat{\omega}_N| \tag{24}$$

is a consistent and robust estimator of the integrated variance in the presence of stochastic volatility, jumps and noise. Furthermore, the price jumps can be determined as

$$\lambda_{2,m} \left(RRG^{\Delta}_{m,BC} - RBV^{\Delta}_{m,BC} \right) \xrightarrow{p} \sum_{i=1}^{N_p(t)} \xi_i^2$$

where $N_p(t)$ cumulates the number of jumps in a given discrete interval. In this paper, we have used (24) to estimate the daily integrated volatility. Given the properties outlined above, the bias-corrected realized range-based bipower variation represents a suitable ex post-measure of the integrated variance. We further note that, by construction, $RBV^{\Delta}_{m,BC}$ is an estimate of the cumulated continuous part of instantaneous volatility plus the contribution from the jumps in volatility, if present.

Sector	Ticker	Company
BANK	**BAC**	Bank of America
	C	Citygroup
	JPM	JP Morgan
	WFC	Wells Fargo
INSURANCE AND FIN. SERVICES	**AXP**	American Express
	GS	Goldman & Sachs
	MET	Met Life
	MS	Morgan Stanley
OIL, GAS AND BASIC MATERIALS	**XOM**	Exxon
	CVX	Chevron
	FCX	Freeport-McMoRan Copper
	NEM	Newmont Mining Corporation
FOOD, BEVERAGE AND LEISURE	**TWX**	Time Warner
	PEP	Pepsi Cola
	KFT	Kraft
	MCD	Mc Donalds
HEALTH CARE AND CHEMICAL	**JNJ**	Johnson & Jonhson
	PFE	Pfizer
	PG	Procter & Gamble
	DD	Du Pont
INDUSTRIAL GOODS	**CAT**	Caterpillar
	BA	Boeing
	HON	Honeywell
	F	Ford
RETAIL AND TELECOMMUNICATIONS	**WMT**	Wall-Mart
	T	AT&T
	HD	Home Depot
	VZ	Verizon
SERVICES	**FDX**	Fed-Ex
	UPS	UPS
	GE	General Electric
	EMR	Emerson Electric
TECHNOLOGY	**AAPL**	Apple
	IBM	International Business Machines
	HPQ	Hewlett Packard
	TXN	Texas Instruments

Table 1: Sector, Companies and Ticker

	HAR				Size		Variance		Intensity			LR	Q_ϵ^5	Q_ϵ^{20}
	μ	ϕ_D	ϕ_W	ϕ_M	ζ_0	ζ_1	η_0	η_1	λ_0	λ_1	ψ			
AAPL	-0.7078^a	0.3837^a	0.2432^a	0.2578^a	0.3057	-0.0045	0.0149	0.0084^a	0.0615	0.8876^a	0.2725^b	0.0000	0.1002	0.2719
AXP	-0.4101^a	0.2683^a	0.4025^a	0.2654^a	0.2577	0.0331^b	0.1279^b	0.0000	0.0675	0.9230^a	0.4857^a	0.0000	0.0001	0.0042
BA	-0.7923^a	0.2409^a	0.3952^a	0.2176^a	0.5613^a	0.0849^a	0.0242^b	0.0061^b	0.0002	0.9986^a	0.0850^b	0.0000	0.0102	0.0603
BAC	-0.7842^a	0.3539^a	0.3389^a	0.1812	0.4191^a	0.0528^b	0.0133	0.0059	0.0035	0.9950^a	0.2282	0.0000	0.0634	0.0682
C	-0.4447^a	0.3581^a	0.4210^a	0.1480^b	0.2077	0.0123	0.2006^a	0.0000	0.0159	0.9793 ^{a}	0.3995	0.0000	0.0019	0.0002
CAT	-0.3781^a	0.3171^a	0.3523^a	0.2638^a	0.3857^b	0.0392	0.2031^b	0.0000	0.0352	0.8844^a	0.3383^b	0.0000	0.0190	0.0601
CVX	-0.3529^a	0.3612^a	0.4980^a	0.0751^b	0.1931^c	0.0278	0.1574^a	0.0000	0.0268	0.9294^a	0.5828^c	0.0000	0.1211	0.0001
DD	-0.5804^c	0.2584^a	0.4389^a	0.1977^a	0.2370	0.0327	0.1086^b	0.0000	0.0032	0.9938^a	0.2359	0.0000	0.0035	0.0154
EMR	-1.2421^c	0.1295	0.3867^a	0.2541^a	0.5157	0.0902	0.0688	0.0000	0.0060	0.9954^a	0.1481^c	0.0000	0.1105	0.2988
F	-0.2460^b	0.2330^a	0.3115^a	0.4001^a	0.0370	0.0026	0.1487^a	0.0000	0.0437	0.9682^a	0.7102^a	0.0000	0.1224	0.0033
FCX	-0.4215^a	0.2735^a	0.3960^a	0.2370^a	0.5251	0.1046	0.1171	0.0000	0.0717	0.8459^a	0.3381^c	0.0000	0.0001	0.0026
FDX	-0.2267^a	0.2405^a	0.3522^a	0.3681^a	1.1470^b	-0.0042	0.0000	0.0000	0.0260	0.2521	0.1183	0.0000	0.0250	0.1184
GE	-0.8444^a	0.2045^a	0.3724^a	0.3068^a	0.2756^a	0.0292^c	0.0847^c	0.0000	0.2565	0.8499^a	0.5777^a	0.0000	0.1922	0.2962
GS	-0.3756^a	0.4233^a	0.3550^a	0.1548^a	0.1660	0.0070	0.1267^a	0.0000	0.0133	0.9699^a	0.4478^b	0.0000	0.0000	0.0000
HD	-0.4401^a	0.2673^a	0.3360^a	0.3236^a	0.7034^c	0.0863	0.0000	0.0056	0.0365	0.8735^a	0.3071^b	0.0000	0.0001	0.0016
HON	-0.7312^a	0.2303^a	0.4108^a	0.2140^a	0.4208	0.0742	0.1459^c	0.0000	0.0008	0.9974^a	0.1390	0.0000	0.0360	0.1009
HPQ	-0.4276^a	0.3037^a	0.4463^a	0.1747^a	0.1692	0.0110	0.1949^b	0.0000	0.0862	0.8467^a	0.3783^b	0.0000	0.0001	0.0068
IBM	-1.0336^a	0.2651^a	0.4528^a	0.1025^a	0.7323^a	0.1169^a	0.0000	0.0040	0.0024	0.9957^a	0.1244^b	0.0000	0.0003	0.0010
JNJ	-0.9385^a	0.2113^a	0.4143^a	0.2293^a	0.7179^b	0.0788^c	0.0329^b	0.0047^c	0.0008	0.9966^a	0.0887	0.0000	0.0092	0.0000
JPM	-0.5679	0.3508^a	0.3292^a	0.2283	0.4209	0.0451	0.0000	0.0047	0.0262	0.9526^b	0.4006	0.0000	0.1982	0.1499
KFT	-0.8325^a	0.1390^a	0.4450^a	0.2533^a	0.6787^b	0.1033^b	0.0654^c	0.0112	0.0035	0.9889^a	0.1474	0.0000	0.0291	0.4929
MCD	-0.7113	0.1910^a	0.4142^a	0.2660^a	1.1870^a	0.1761^a	0.0000	0.0125	0.0015	0.9912^a	0.0972	0.0000	0.0315	0.0199
MET	-0.4359^a	0.2099^a	0.4333^a	0.2830^a	0.4830	0.0356	0.0000	0.0071	0.0364	0.8780^a	0.4684	0.0000	0.1140	0.3253
MS	-0.2929^b	0.3958^a	0.3142^a	0.2380^a	0.2663	0.0106	0.2168	0.0000	0.0295	0.9055^a	0.5383^b	0.0000	0.0675	0.3521
NEM	-0.2385^a	0.3121^a	0.4559^a	0.1817^a	0.5149^a	0.0358	0.0000	0.0126^b	0.0000	0.9966^a	0.1028^b	0.0000	0.3211	0.2015
PEP	-0.7304^a	0.1514^a	0.4264^b	0.3062^a	1.3219^b	0.1601^b	0.0000	0.0044	0.0342	0.8268^b	0.1989	0.0000	0.0177	0.1463
PFE	-0.2931^a	0.3047^a	0.3461^a	0.3081^a	-0.1343	-0.1166	0.5058^a	0.0000	0.1283^b	0.3296	0.3296^b	0.0000	0.0644	0.0739
PG	-0.6067^a	0.2976^a	0.4038^a	0.1969^a	0.3015	0.0393	0.2008^a	0.0000	0.0200	0.9575^a	0.2514^a	0.0000	0.0242	0.1525
T	-0.5487^a	0.2067^a	0.4618^a	0.2228^a	0.3867^a	0.0736^b	0.1633^a	0.0000	0.0040	0.9929^a	0.1861^b	0.0000	0.0001	0.0049
TWX	-0.5917^a	0.1915^a	0.3770^a	0.3221^a	0.3650^b	0.0519	0.1721^a	0.0000	0.0071	0.9859^a	0.2004	0.0000	0.0125	0.0329
TXN	-0.3598^a	0.2417^a	0.4403^a	0.2391^a	0.1421	0.0217	0.1545^b	0.0000	0.0033	0.9900^a	0.3371^a	0.0000	0.1688	0.0013
UPS	-0.4108^a	0.2537^a	0.5057^a	0.1711^a	0.2225	-0.0048	0.2970^a	0.0000	0.0010	0.9921^a	0.1178	0.0000	0.0199	0.0580
VZ	-0.4868^a	0.2415^a	0.3736^a	0.3095^a	0.2490	0.0010	0.2056^a	0.0000	0.1336	0.6782	0.6782	0.0000	0.0016	0.0265
WFC	-0.6782^a	0.2174^a	0.3597^a	0.3194^a	0.3027^b	0.0418^b	0.0610^a	0.0000	0.1311	0.9109^a	0.5328^a	0.0000	0.1217	0.1860
WMT	-0.5040^a	0.1984^a	0.4777^a	0.2397^a	0.4295^c	0.0528	0.2330^c	0.0000	0.0044	0.9868^a	0.1487^b	0.0000	0.0018	0.0052
XOM	-0.5518^a	0.3671^a	0.4096^a	0.1270^a	0.5079^a	0.0749	0.0193^b	0.0046	0.0165	0.9617^a	0.3341^b	0.0000	0.0399	0.0002

Table 2: Estimated parameters of the HAR-V-J model using price data from January 2, 2004 to December 31, 2009 using data on companies in Table 1. Q_ϵ^5 and Q_ϵ^{20} are the p-values of the Ljung-Box test on the residuals, with 5 and 20 lags, respectively.

	$\bar{\sigma}$	Skewness	Kurtosis	$\Lambda_{\sigma,t}$	$\overline{\mathrm{E}(N_{\sigma,t}\|I^t)}$	$\overline{\mathrm{Var}(X_t\|I^{t-1})}$	$\overline{\mathrm{Sk}(X_t\|I^{t-1})}$	$\overline{\mathrm{Kur}(X_t\|I^{t-1})}$	$\rho(J_{t\|t-1},\Xi_t)_{04:07}$	$\rho(J_{t\|t-1},\Xi_t)_{08:09}$	$\rho(J_{t\|t-1},\Xi_t)_{04:09}$
AAPL	24.8368	0.7437	4.5830	0.5912	0.6087	0.3901	0.3987	3.6422	0.2818	0.5648	0.4725
AXP	20.5084	0.7587	2.4834	0.9095	0.9133	0.2857	0.2257	3.7675	0.5104	0.5782	0.6132
BA	15.9610	1.1382	4.7531	0.3808	0.3877	0.2337	0.1963	3.6179	0.2682	0.6230	0.6784
BAC	23.1555	0.9767	2.9254	0.6856	0.6890	0.3076	0.2799	3.8029	0.6742	0.5254	0.6139
C	23.9415	0.9290	3.0168	0.6694	0.6751	0.3356	0.2524	3.8572	0.6441	0.5072	0.5660
CAT	18.4294	1.1565	4.1235	0.3099	0.3112	0.2298	0.3595	4.0305	0.3245	0.4436	0.4644
CVX	15.9767	0.9214	4.7157	0.4063	0.4085	0.1963	0.1205	3.7438	0.4233	0.5172	0.5182
DD	16.5392	1.1019	4.1269	0.7319	0.7387	0.2351	0.1533	3.5152	0.4406	0.6532	0.7190
EMR	16.3422	1.3718	5.3417	1.2850	1.2832	0.2851	0.1308	3.5041	0.5972	0.6050	0.6462
F	30.0859	1.2691	5.7290	1.4755	1.4805	0.3152	0.0982	4.1787	0.1774	0.3613	0.4006
FCX	29.1566	1.0974	4.6910	0.4681	0.4694	0.2165	0.2277	3.6583	0.4898	0.4575	0.5244
FDX	16.0122	0.7384	3.4815	0.0347	0.0343	0.1703	0.7518	5.1168	0.1743	0.1579	0.1249
GE	15.6763	1.1663	3.7924	1.7294	1.7348	0.4168	0.2236	3.3658	0.5014	0.6248	0.6820
GS	21.5953	1.0772	3.7746	0.5040	0.5068	0.2280	0.2076	3.5382	0.6845	0.5542	0.5718
HD	17.8131	0.9366	3.4931	0.2877	0.2871	0.2472	0.3059	3.6000	0.3987	0.4311	0.4774
HON	16.7893	1.3807	6.2263	0.5174	0.5244	0.2223	0.1286	3.6710	0.2108	0.7155	0.7299
HPQ	16.6975	1.1293	4.8690	0.5652	0.5659	0.2683	0.2787	4.0253	0.0889	0.4906	0.4080
IBM	13.3862	1.3166	5.2915	0.5433	0.5439	0.2431	0.1546	3.6105	0.5349	0.7401	0.7665
JNJ	10.1048	1.3872	5.7007	0.3134	0.3160	0.2594	0.3418	3.8294	0.2928	0.5047	0.5276
JPM	22.0841	0.9047	2.7714	0.5469	0.5456	0.2699	0.2641	3.6057	0.6301	0.6249	0.6702
KFT	16.1119	0.6633	5.0948	0.3053	0.3050	0.2926	0.3052	4.2472	0.3070	0.5493	0.4734
MCD	14.1048	1.3491	6.3214	0.1670	0.1660	0.2369	0.3924	4.3833	0.2920	0.5171	0.5447
MET	23.0263	1.1781	4.1188	0.3026	0.3034	0.2714	0.3183	3.6601	0.4541	0.5738	0.5745
MS	28.5541	1.1187	3.8033	0.3229	0.3238	0.2515	0.3450	3.9759	0.6088	0.5818	0.5781
NEM	21.5460	0.8662	3.8108	0.0705	0.0708	0.1430	0.2162	3.6245	0.3328	0.7939	0.7438
PEP	11.7077	1.4604	6.2378	0.1976	0.1975	0.2463	0.4442	3.8648	0.3191	0.2381	0.2741
PFE	13.8933	1.2437	4.9546	0.1913	0.1910	0.3132	0.8304	5.8044	0.1170	0.2271	0.1869
PG	11.5246	1.3308	5.6124	0.4880	0.4902	0.2382	0.2083	4.1404	0.2384	0.5714	0.5826
T	17.0254	0.8767	4.9206	0.6563	0.6631	0.2207	0.0546	4.3048	0.4208	0.6278	0.6486
TWX	17.6097	1.1112	4.6496	0.5342	0.5365	0.2472	0.2715	3.9903	0.3169	0.4146	0.4825
TXN	20.3096	0.9976	4.2807	0.3593	0.3640	0.1838	0.0809	3.5777	0.0486	0.4574	0.5273
UPS	13.1429	1.0870	4.4766	0.1774	0.1806	0.2081	0.3284	4.1450	0.2766	0.4385	0.4826
VZ	14.5341	1.2889	5.2242	0.4165	0.4168	0.2957	0.4046	3.9586	0.2169	0.3585	0.3378
WFC	22.6472	0.8660	2.6464	1.5105	1.5158	0.3363	0.1567	3.3092	0.6653	0.6064	0.6815
WMT	13.1333	1.1507	4.4018	0.3489	0.3511	0.2430	0.2992	4.1274	0.4515	0.6019	0.6349
XOM	15.1828	0.9625	4.5853	0.4153	0.4133	0.2221	0.1888	3.6521	0.5374	0.5359	0.5576

Table 3: Summary statistics of $\log(RBV_{BC})$, and conditional jumps and conditional moments of log-volatility. First column reports the average percentage volatility on annual basis, that is $\bar{\sigma} = \frac{1}{T}\sum_{t=1}^{T}\sqrt{RBV_{BC,t}} \times 100 \times \sqrt{252}$. Second and third columns report sample skewness and kurtosis of $\log(RBV_{BC})$, while column 4 reports the sample averages of $\Lambda_{\sigma,t}$, which is the ex-post average number of jumps. $\overline{E(N_{\sigma,t}|I^t)}$, $\overline{\mathrm{Var}(X_t|I^{t-1})}$, $\overline{\mathrm{Sk}(X_t|I^{t-1})}$, $\overline{\mathrm{Kur}(X_t|I^{t-1})}$ are the sample average of the number of expected jumps, and the sample average of the conditional variance, conditional skewness, and conditional kurtosis of log-volatility, respectively. The last three columns report the jump correlations for the periods 2004-2007, 2008-2009 and 2004-2009. $J_{t|t-1} = E[J_t|I^{t-1}]$ is the expected jump component in the $BPV_{BC,t}$, that is obtained from the estimates of the HAR-V-J model. Squared jump price is estimated by $\Xi_t = \lambda_{2,m}\,(RRG_{BC} - RBV_{BC}).\rho(J_{t|t-1},\Xi_t)$ is the estimated linear correlation coefficient between $J_{t|t-1}$ and Ξ_t.

	October 10, 2005			October 10, 2008		
	$P(ARBV_t^{HAR} > u_1 \| I^{t-1})$	$P(ARBV_t^{HAR-V-J} > u_1 \| I^{t-1})$	$ARBV$	$P(ARBV_t^{HAR} > u_2 \| I^{t-1})$	$P(ARBV_t^{HAR-V-J} > u_2 \| I^{t-1})$	$ARBV$
AAPL	0.0192	0.1927	20.018	0.0003	0.3425	140.41
AXP	0.0000	0.0006	7.0985	0.0026	0.4233	195.99
BA	0.0000	0.0000	11.243	0.0000	0.2015	123.42
BAC	0.0000	0.0000	7.2908	0.3794	0.4587	199.49
C	0.0000	0.0256	9.5267	0.5227	0.4598	255.54
CAT	0.0000	0.0000	11.985	0.0000	0.2567	152.80
CVX	0.0000	0.0345	15.954	0.0000	0.3070	192.10
DD	0.0000	0.0000	9.8212	0.0000	0.4173	141.288
EMR	0.0000	0.1101	11.040	0.0000	0.4098	131.84
F	0.0042	0.2953	37.966	0.1033	0.4951	411.70
FCX	0.0000	0.0067	26.114	0.0371	0.2950	211.29
FDX	0.0000	0.0000	12.231	0.0000	0.0000	93.876
GE	0.0000	0.2338	6.8006	0.0000	0.4823	153.02
GS	0.0000	0.0000	7.7381	0.0008	0.4405	272.77
HD	0.0000	0.0115	10.228	0.0000	0.1785	171.78
HON	0.0000	0.0000	13.446	0.0000	0.3047	150.39
HPQ	0.0000	0.0095	14.704	0.0000	0.1808	110.80
IBM	0.0000	0.0000	11.742	0.0000	0.2861	137.97
JNJ	0.0000	0.0000	9.6341	0.0000	0.0754	104.80
JPM	0.0000	0.0000	10.824	0.0164	0.3880	206.86
KFT	0.0000	0.0000	14.908	0.0000	0.0810	100.54
MCD	0.0000	0.0000	6.8773	0.0000	0.0403	146.53
MET	0.0000	0.0009	12.861	0.1398	0.3513	147.97
MS	0.0000	0.0000	10.599	1.0000	0.7211	554.00
NEM	0.0000	0.0000	19.685	0.0000	0.0549	126.45
PEP	0.0000	0.0007	9.6105	0.0000	0.0303	139.31
PFE	0.0000	0.0025	12.018	0.0000	0.0390	115.89
PG	0.0000	0.0003	8.5149	0.0000	0.1910	125.75
T	0.0000	0.0000	21.816	0.0000	0.2640	152.20
TWX	0.0000	0.0258	16.411	0.0000	0.3118	140.85
TXN	0.0000	0.0005	22.996	0.0000	0.2323	115.72
UPS	0.0000	0.0000	11.672	0.0000	0.0672	164.68
VZ	0.0000	0.0515	12.141	0.0000	0.2131	134.75
WFC	0.0000	0.0797	8.0200	0.2204	0.4765	204.32
WMT	0.0000	0.0000	9.5837	0.0000	0.1092	129.32
XOM	0.0000	0.0298	13.064	0.0000	0.3178	188.56

Table 4: Probability of tail events. $ARBV$ is the annualized percentage RBV, $P(ARBV_t^{HAR} > u_1|I^{t-1})$ and $P(ARBV_t^{HAR-V-J} > u_1|I^{t-1})$ are the estimated conditional probabilities obtained from the HAR and HAR-V-J model, respectively. u_1 and u_2 represent the threshold values and correspond to a volatility level expressed in annual percentage, where $u_1 = 30\%$ and $u_2 = 120\%$.

	const	ΔV_{t-1}	ΔCM_{t-1}	ΔEx_{t-1}	$\Delta S\&P_{t-1}$	ΔVIX_{t-1}	CS_{t-1}	TS_{t-1}	FF_{t-1}	CDS_{t-1}
AAPL	1.3792^a	0.0095	-0.7881^a	0.3200	-0.7085	0.0121	-0.0691^a	-0.0144^b	-0.1326^b	0.0622b
AXP	1.1161^a	0.0047	-1.0269^c	0.4968	0.4831	0.2246^c	0.0407	-0.0367^a	-0.1776^c	0.1173^a
BA	0.9648^a	0.0218^c	-0.7517	0.1320	0.0667	0.0813	0.0892^c	-0.0035	-0.4176^a	0.0726^a
BAC	0.8668^a	0.0594	-2.0748^b	2.1998	-0.5725	0.0820	0.2429^b	-0.0223^c	-0.1059	0.2600^a
C	1.0193^a	0.0033	-0.5882	1.7527	0.0558	0.1822	0.0939	-0.0078	-0.3623^a	0.1319^a
CAT	1.0832^a	0.0104	-0.9742^b	0.5977	-0.2300	0.0910	0.0192	-0.0098^b	-0.0975	0.0442^a
CVX	1.0776^a	-0.0105	-0.2123^b	-0.0425	-0.0188	0.0828	-0.0063	-0.0178^a	-0.2029^a	0.0294^b
DD	1.0225^a	-0.0299	-0.3143	-0.2375	-0.3065	0.0175	0.0724	-0.0174^a	-0.4577^a	0.0515^a
EMR	0.9382^a	0.1023^a	-3.604^b	1.9005^c	0.9957	0.5067	0.1890^a	-0.0034	-1.0732^a	0.1019^b
F	1.0284^a	-0.0006	-0.1775	-0.0059	0.0388	0.0240	0.0868^b	-0.0045	-0.2235^b	0.0635^a
FCX	1.0880^a	0.0580^b	-2.5130^b	0.6055	1.1163	0.2667	-0.0122	-0.0176^a	-0.1922	0.1050^a
FDX	1.0853^a	0.0028	-0.1436	0.0179	0.2656	0.0841^b	-0.0056^c	-0.0028^b	-0.0061	0.0078^b
GE	1.1700^a	0.0975^b	-1.9431	2.2982	1.0702	0.5062	0.0850	-0.0105	-0.1300	0.2196^a
GS	1.1100^a	0.0118	-0.5945	0.2205	-0.3457	0.0394	-0.0329	-0.0193^a	-0.4037^a	0.0946^a
HD	1.1443^a	0.0155	-1.9854^b	1.1995^c	1.0467	0.2723^c	-0.0330	-0.0122^a	-0.2653^a	0.0752^a
HON	0.9871^a	0.0263^c	-1.1943^c	0.1126	-0.4013	0.0609	0.0863^a	-0.0140^a	-0.4581^b	0.0349^b
HPQ	1.1454^a	0.0005	-0.1460	0.4508	-0.4486	-0.0269	-0.0018	-0.0081^b	-0.1227^a	0.0163^b
IBM	1.0089^a	0.0863^b	-2.5584^c	0.6803	-1.2299	0.0814	0.0827^b	-0.0255^a	-0.6592^a	0.1052^a
JNJ	0.9726^a	0.0079	-1.2234^b	0.9297	0.1176	0.0869	0.1637^a	-0.0200^a	-0.5588^a	0.2480^b
JPM	1.1029^a	0.0539^c	-2.6112^a	3.0747^c	1.4745	0.3724	0.0186	-0.0369^a	-0.1146	0.2032^a
KFT	1.1354^a	-0.0353^b	-0.0596	-0.3737	0.4794	0.0820	0.0129	-0.0250^a	-0.4526^a	0.0258^b
MCD	1.0686^a	-0.0839^c	0.2238	-1.1521	1.3434	0.0701	0.0278	-0.0168^a	-0.6116^a	0.0397^b
MET	1.1410^a	-0.0725^c	-1.1698	2.2196	-0.9290	-0.1201	-0.0266	-0.0224^b	-0.4281^a	0.1160^a
MS	1.1724^a	-0.1021^a	-0.1095	1.4856	1.1519	0.1853	-0.0901	-0.0188^b	-0.4400^a	0.1310^b
NEM	1.0239^a	-0.0004	-01369	0.1479	-0.3154	-0.0167	0.00735	-0.0103^a	-0.2092^a	0.0259^a
PEP	1.1183^a	-0.0264	-1.5286	0.1227	2.4557	0.2662	-0.0004	0.00465	-0.6577	0.0447
PFE	1.2602^a	0.0204	0.0249	-0.1476	0.0999	0.0220	-0.0309^a	-0.0018	0.03225^b	-0.0033
PG	1.0901^a	0.0168^c	-0.8264^b	0.0146	-0.0259	0.1022	0.0122	-0.0137^a	-0.3368^a	0.0271^b
T	1.0463^a	0.0250	-1.0207^c	0.3922	-0.2814	0.1311	0.0313	-0.0183^a	-0.3986^a	0.0525^b
TWX	1.0066^a	0.0108	-0.8387	-0.1065	-0.6888	0.0552	0.0928^a	-0.0012	-0.3599^a	0.0416^b
TXN	1.0213^a	-0.0038	-0.2745	-0.2487	-0.1945	-0.0037	0.0154	-0.0074^a	-0.2249^a	0.0235^a
UPS	1.0179^a	-0.0010	-0.2146	0.0815	-0.5324^c	-0.0559	0.0721^a	-0.0191^a	-0.2877^a	0.0098
VZ	1.1977^a	0.0273	-1.1908^b	0.1935	0.8698	0.3347^a	-0.0132	-0.0130^c	-0.0814	0.0415^a
WFC	1.0336^a	0.0991^b	-2.8658^b	3.1047	0.5176	0.3307	0.1291	-0.0426^a	-0.0001	0.2736^a
WMT	1.0959^a	0.0114	-0.5558	0.0114	-0.3939	0.0045	0.0017	-0.0090^c	-0.3650^a	0.0415^a
XOM	1.1229^a	0.0510^c	-2.2317^c	-0.0245	0.1617	0.2591^c	-0.0279	-0.0269^a	-0.2820^b	0.0849^a

Table 5: Estimated conditional jump for each stock is regressed on the lagged values of the S&P volume change, ΔVolumes; the daily log return of S&P, ΔS&P; the log return of the DJ-UBS Commodity Index, ΔCommodity; the first difference of the logarithm of the foreign exchange value of the US dollar, ΔExchange; the first difference of the logarithm of the foreign exchange value of the volatility index VIX, ΔVIX; the credit spread, CS; the term spread, TS; the difference between the effective and the target Federal Funds rates, FF; the US Banks sector credit default swap index, CDS. a, b, and c stand for significance at 1%, 5% and 10% respectively.

(a) All stocks

	β	s.e.	t-stat	p-value	r^2
const	-2.2264	0.5062	-4.398	0.0000	
ΔVolume$_{t-1}$	0.3543	0.3118	1.136	0.2560	0.0094
ΔCommodity$_{t-1}$	-26.7892	13.075	-2.049	0.0406	0.0002
ΔExchange$_{t-1}$	12.0329	17.988	0.669	0.5036	0.0001
ΔS&P$_{t-1}$	-0.9740	18.837	-0.052	0.9588	0.0001
ΔVIX$_{t-1}$	3.2619	2.9468	-1.107	0.2685	0.0001
CS_{t-1}	0.8990	0.5610	1.603	0.1092	0.0132
TS_{t-1}	-0.4454	0.1415	-3.147	0.0017	0.0172
FF_{t-1}	-9.0329	2.5498	-3.542	0.0004	0.1557
CDS_{t-1}	1.8061	0.5181	3.485	0.0005	0.1690

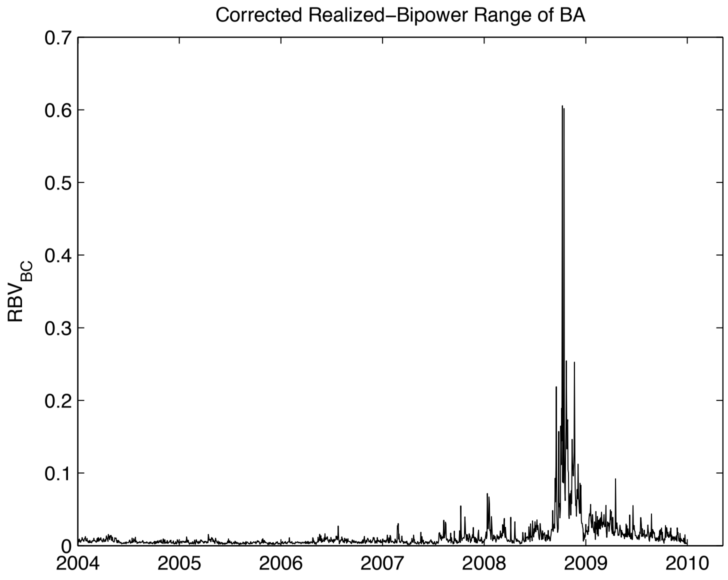
(b) Excluding the Financial Sector

	β	s.e.	t-stat	p-value	r^2
const	-1.9010	0.4182	-4.545	0.0000	–
ΔVolume$_{t-1}$	0.2918	0.2613	1.117	0.2643	0.0082
ΔCommodity$_{t-1}$	-24.6809	12.569	-1.964	0.0498	0.0002
ΔExchange$_{t-1}$	5.8724	15.405	0.381	0.7031	0.0001
ΔS&P$_{t-1}$	-0.7386	16.863	-0.044	0.9651	0.0001
ΔVIX$_{t-1}$	2.7413	2.3651	1.159	0.2466	0.0002
CS_{t-1}	0.8922	0.4415	2.021	0.0435	0.0162
TS_{t-1}	-0.3806	0.1239	-3.071	0.0022	0.0157
FF_{t-1}	-9.0319	2.6003	-3.473	0.0005	0.1768
CDS_{t-1}	1.3005	0.3895	3.339	0.0009	0.1314

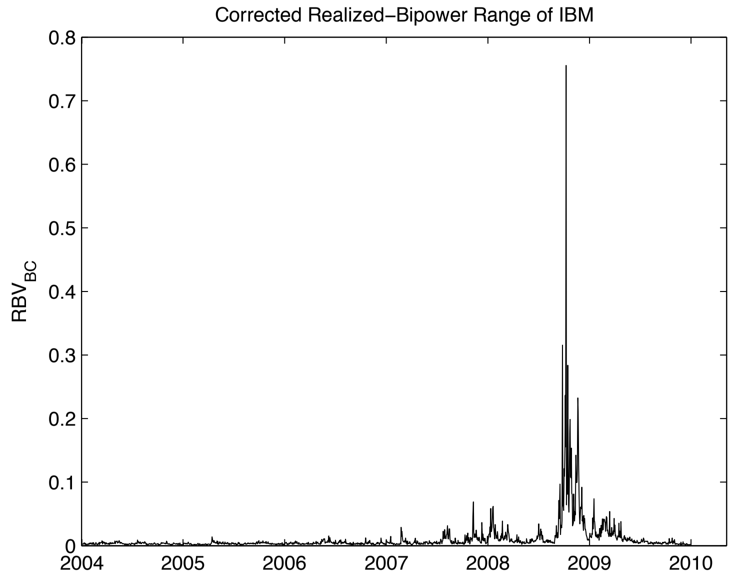
Table 6: OLS regression: The first principal component of the excess jump, PC_1, is regressed on the lagged values of the S&P volume change, ΔVolumes; the daily log return of S&P, ΔS&P; the log return of the DJ-UBS Commodity Index, ΔCommodity; the first difference of the logarithm of the foreign exchange value of the US dollar, ΔExchange; the first difference of the logarithm of the foreign exchange value of the volatility index VIX, ΔVIX; the credit spread, CS; the term spread, TS; the difference between the effective and the target Federal Funds rates, FF; the US Banks sector credit default swap index, CDS. The Newey-West standard errors, with a a Bartlett kernel with bandwidth 9, are reported. The last column reports the partial r^2. The Financial Sector is given by the sum of the Bank and Insurancce sectors.

	HAR				Size			Variance		Intensity				Diebold-Mariano	
	μ	ϕ_D	ϕ_W	ϕ_M	ζ_0	ζ_1	ζ_2	η_0	η_1	λ_0	λ_1	ψ	β_1	MSE	MAE
AAPL	-0.6544	0.3528	0.2642^a	0.2525^a	0.2503	0.0000	0.0833	0.0000	0.0115	0.0430	0.9043^a	0.2226	0.0000	-2.2817^b	-1.8900^c
AXP	-0.9334	0.2108^a	0.3512^a	0.2881v	0.0723	0.0000	0.0630^b	0.0011	0.0037	0.0234	0.9635^a	0.4911^a	0.0429	-1.8051^c	-2.8538^a
BA	-0.8688^a	0.2466^a	0.3904^a	0.2019^a	0.2892^a	0.0474	0.0526^b	0.0300	0.0044	0.0000	0.9895^a	0.0955^c	0.0015	-1.9332^b	-1.1366
BAC	-0.7531^c	0.3529^a	0.3133^a	0.2127^a	0.2210^b	0.0220	0.0597^c	0.0088^c	0.0065^a	0.0078^b	0.9562^a	0.3770^a	0.0359	-1.7569^c	-1.3594
C	-1.3239^a	0.3188^a	0.2509^b	0.2415^a	-0.0007	-0.0068	0.0594^a	0.0347^a	0.0000	0.4631^b	0.9019^a	0.7501^a	0.0837	-2.3463^a	-2.3963^a
CAT	-0.4204	0.3410	0.3478^a	0.2361	-0.1528	-0.0425	0.1308	0.1508	0.0000	0.0640	0.8324^b	0.4192	0.0156	-2.5369^a	-1.2377
CVX	-0.3858^a	0.3814^a	0.4891^a	0.0584	-0.0411	-0.0084	0.0621^b	0.1030^a	0.0000	0.0266	0.9631^a	0.4256	0.0000	-2.2720^b	-1.9342^b
DD	-0.7796	0.2811^a	0.4217^a	0.1569	-0.0101	-0.0067	0.0541	0.0670	0.0000	0.0111	0.9820^a	0.3594	0.0148	-2.4019^a	-1.7211^c
EMR	-1.5402^a	0.1669^b	0.3439^a	0.2055^a	0.1614	0.0290	0.0789^c	0.0472	0.0000	0.0255	0.9848^a	0.2605	0.0054	-1.3819	-0.6956
F	-0.2408^a	0.2561^a	0.3049^a	0.3840^a	-0.0149	-0.0062	0.0139	0.1362^a	0.0000	0.0487	0.9070^a	0.8047^a	0.1248^b	-0.8130	-0.1861
FCX	-1.0258^a	0.1784^a	0.3774^a	0.1910^a	0.1594^a	0.0409^a	0.0146^b	0.0356^a	0.0000	1.0402^b	0.7319^a	0.3997^c	0.0385	-0.7793	-2.1887^b
FDX	-0.8878^a	0.2382^a	0.2215^a	0.3986^a	0.0355	0.0021	0.0189^b	0.0303	0.0000	1.0083^a	0.8002^a	0.4154^a	0.0137^b	-1.5909	-0.0553
GE	-1.1952^a	0.2197^a	0.3465^a	0.2635^a	0.0056	-0.0081	0.0615^a	0.0416	0.0004	0.3500^b	0.8433^a	0.7753^a	0.1079	-2.8583^a	-3.1554^a
GS	-0.4342^a	0.4406^a	0.3381^a	0.1451^b	-0.1063	-0.0316	0.0912	0.0810^b	0.0000	0.0177	0.9681^a	0.4955^c	0.0073	-1.6687^c	-0.6083
HD	-0.8437^b	0.3135^a	0.3178^a	0.2330^a	-0.0621	-0.0173	0.0614^a	0.0307	0.0004	0.3627^b	0.8801^a	0.7802^a	0.0060	-1.8166^c	-1.6948^c
HON	-2.0460^a	0.2188^a	0.2520^a	0.1791^a	0.0899	0.0098	0.0165	0.0231	0.0000	0.7140^b	0.8954^a	0.4399^b	0.0000	-1.4886	-0.8323
HPQ	-0.5308^b	0.3381^a	0.4246^a	0.1414^a	-0.1601	-0.0361	0.0930^c	0.1262^c	0.0004	0.1638	0.8184^a	0.5141^b	0.0000	-1.3399	-1.1274
IBM	-0.6852^a	0.3187^a	0.3806^a	0.1403^a	0.2592	0.0220	0.0773^b	0.0112	0.0300	0.0082	0.9405^a	0.3089^b	0.0027	0.8789	-0.8333
JNJ	-1.8705^a	0.1267^a	0.4915^a	0.1302^a	0.1640^a	0.0150^b	0.0135^c	0.0332^a	0.0000	0.0786	0.9809^a	0.0916	0.0105	-2.001^b	-0.2864
JPM	-0.7551^a	0.3957^a	0.3469^a	0.1493^a	-0.0562	-0.0140^b	0.0707^a	0.0339^b	0.0000	0.2501^c	0.9367^a	0.4807^a	0.0000	-3.7057^a	-3.2211^a
KFT	-0.6361^b	0.1498	0.4794^a	0.2564^a	0.3692	0.0000	0.1272	0.0000	0.0121	0.1424	0.2284	0.2284	0.0050	-0.1795	0.9687
MCD	-0.8048	0.1911^a	0.4017^a	0.2608^a	0.6072	0.0870	0.0836	0.0000	0.0108	0.0031	0.9767^a	0.1570	0.0029	-0.7961	-0.2937
MET	-0.5430^a	0.1938^a	0.4455^a	0.2664^a	0.3094	0.0081	0.0091	0.0000	0.0068	0.0284	0.7854^a	0.5655^c	0.0722	-2.7892^a	-2.3753^b
MS	-1.0449^a	0.3305^a	0.2360^a	0.2669^a	0.0306	0.0000	0.0416^a	0.0257^a	0.0000	0.4769	0.9033^a	0.6939^b	0.0340	-2.3952^b	-2.5902^a
NEM	-0.2565^a	0.3124^a	0.4476^a	0.1866^a	0.0956	0.0000	0.1279^c	0.0000	0.0107	0.0002	0.9931^a	0.1532	0.0008	-1.1651	-0.2433
PEP	-0.8087^a	0.1645^a	0.4309^a	0.2755^a	0.1387	0.0000	0.1597^a	0.1346	0.0000	0.0874	0.7582	0.3919	0.0037	-1.6983^b	-1.4271
PFE	-0.5462^a	0.3136	0.3081	0.2917^a	0.1299	0.0000	0.0553	0.2156	0.0000	0.2211	0.5350	0.3224	0.0459	-0.9904	-1.7955^c
PG	-0.7598^a	0.3002^a	0.3912^a	0.1800^b	0.0000	0.0015	0.1161	0.1629	0.0000	0.0215	0.9594^a	0.2452	0.0015	-1.8726^b	-1.01111
T	-0.6127^a	0.2185^a	0.4561^a	0.2016^a	0.1667	0.0436	0.0771^b	0.1480^a	0.0000	0.0000	0.9989^a	0.2228^B	0.0036	0.0681	0.7362
TWX	-1.0733^a	0.1831^a	0.3840^a	0.2533^a	0.0710^c	0.0066	0.0140^c	0.0370	0.0000	0.1837^c	0.9482^a	0.2776	0.0441	-1.6202^c	-0.0071
TXN	-0.7930^a	0.2349^a	0.4247^a	0.1666^c	0.0000	0.0043	0.0512	0.0380^a	0.0015	0.0000	0.9970^a	0.3937	0.0091	-1.3336	-1.0804
UPS	-0.5461^c	0.2403^a	0.5081^a	0.1581	0.0349	0.0000	0.1029	0.1733	0.0000	0.0019	0.9873^a	0.1680	0.0031	-1.7430^a	-1.0786
VZ	-0.6593^b	0.2312^a	0.3752^a	0.2865^a	0.1307	0.0000	0.0818	0.1608	0.0001	0.1597	0.6632^a	0.6632^c	0.0303	-1.0912	-1.3768
WFC	-0.8173^b	0.2321^a	0.3080^a	0.3293^a	0.0840	0.0000	0.0706^b	0.0023	0.0033	0.0170	0.9459^a	0.6397^b	0.0644	-2.5976^a	-3.2063^a
WMT	-0.5617^a	0.2066^a	0.4762^a	0.2232^a	0.1388	0.0127	0.0584^b	0.1820	0.0000	0.0060	0.9819^a	0.1720^c	0.0033	-1.5982	-1.5337
XOM	-0.5988^a	0.3851^a	0.4046^a	0.1057^a	0.1523	0.0209	0.0901^a	0.0050	0.0042^b	0.0144	0.9753^a	0.3037^b	0.0000	-1.0549	-1.0751

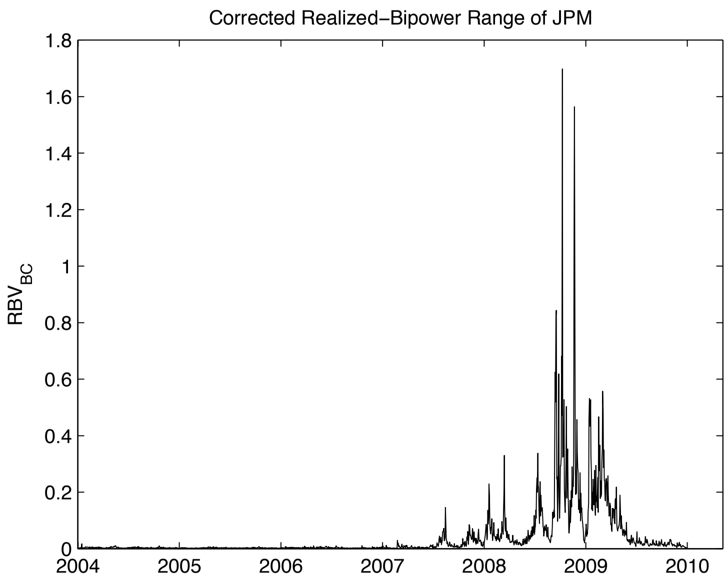
Table 7: Estimated parameters of the model with unobserved jump intensity and size specified as in (17) and (18). a, b, and c stand for significance at 1%, 5% and 10% respectively. Table also reports the in-sample Diebold-Mariano test The loss functions are the mean squared error, MSE, and the mean absolute error, MAE. Negative values represent under-performance of HAR with respect to HAR-V-J .



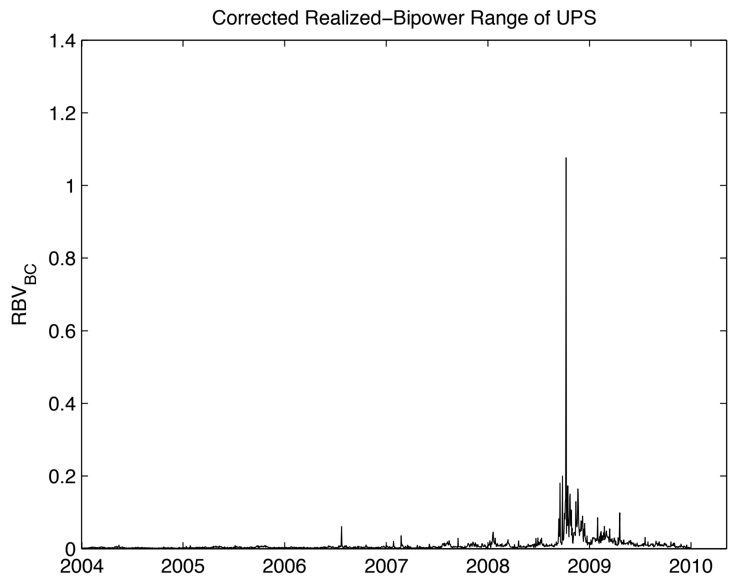
(a) BA



(b) IBM

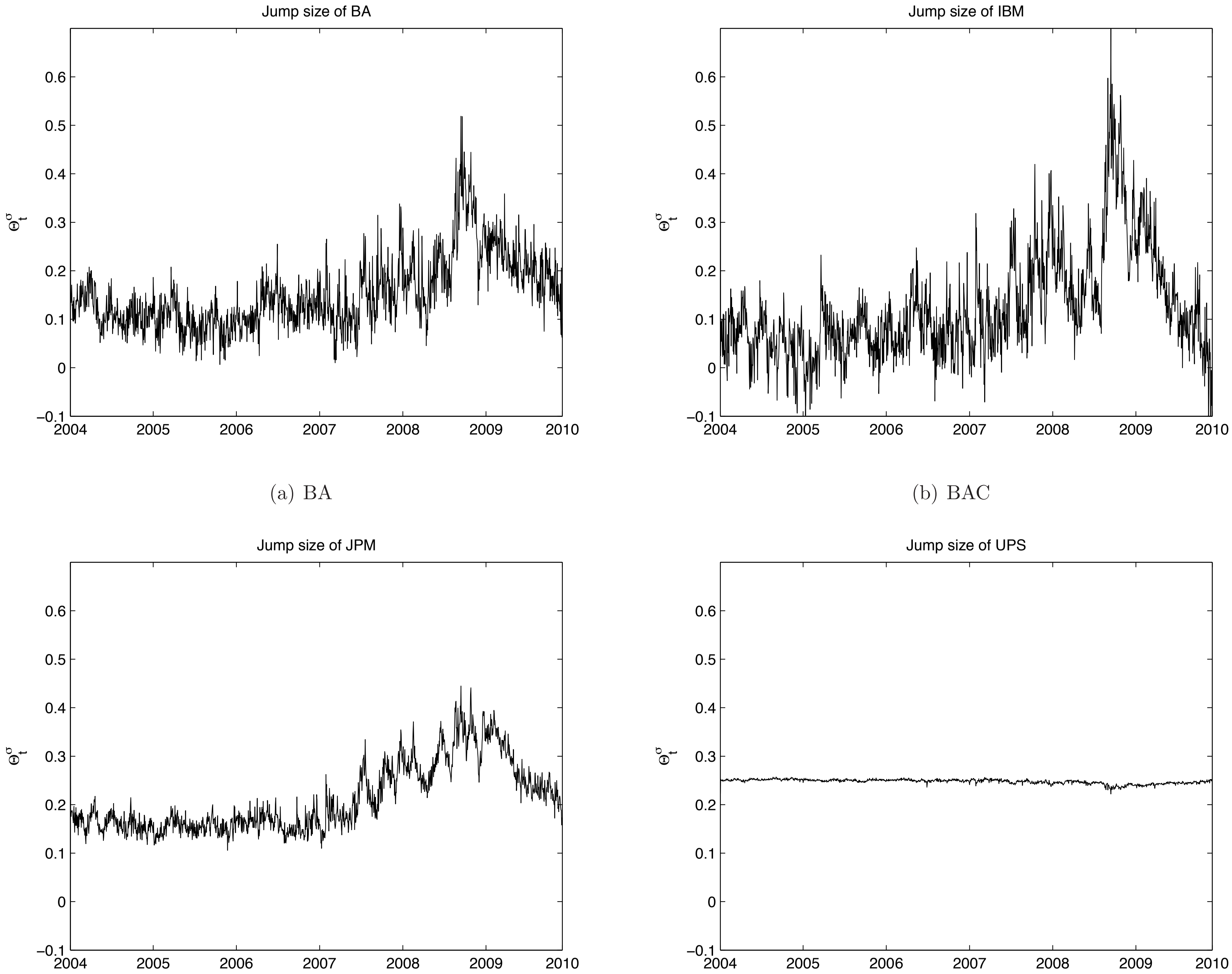


(c) JPM



(d) UPS

Figure 1: Bias corrected range-based bipower variation



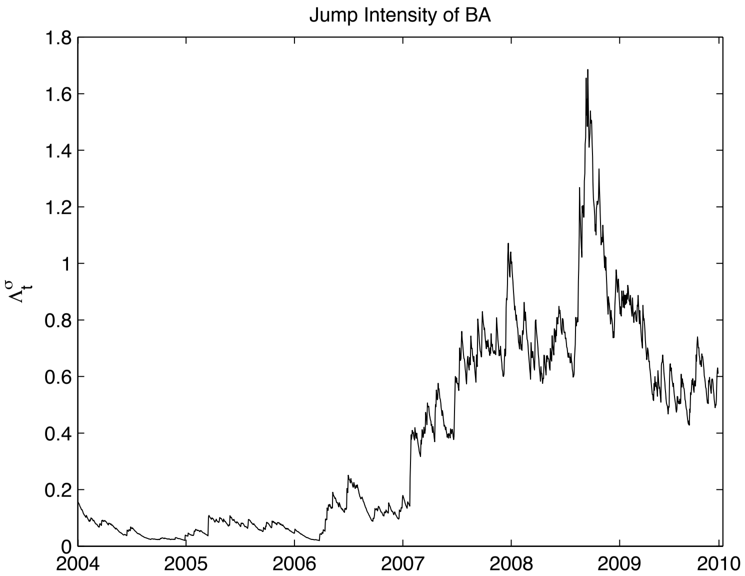
(a) BA

(b) BAC

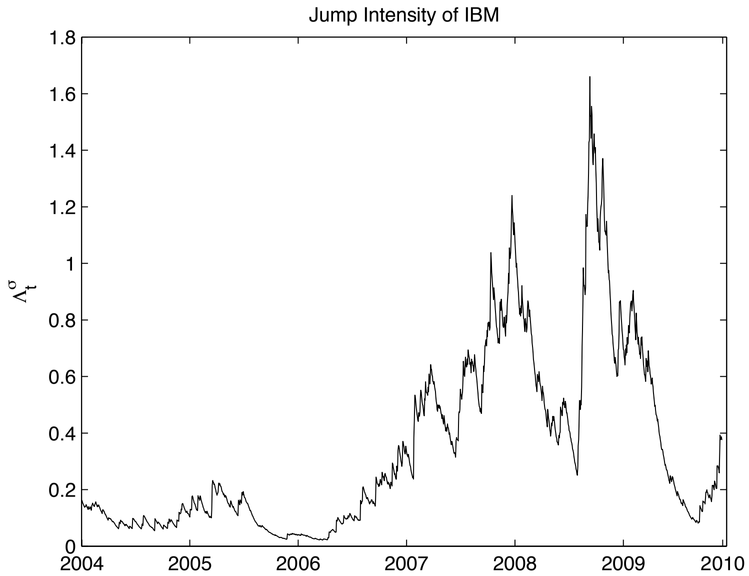
(c) JPM

(d) UPS

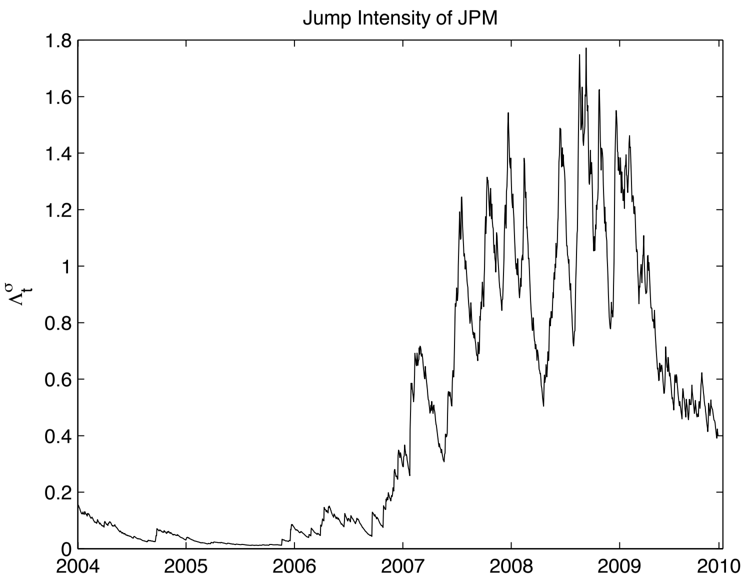
Figure 2: The expected jump size, Θ_t^σ



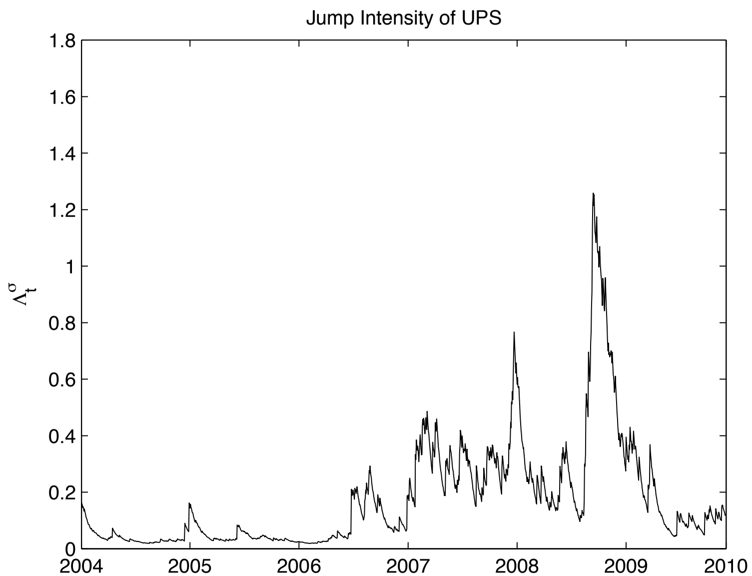
(a) BA



(b) IBM

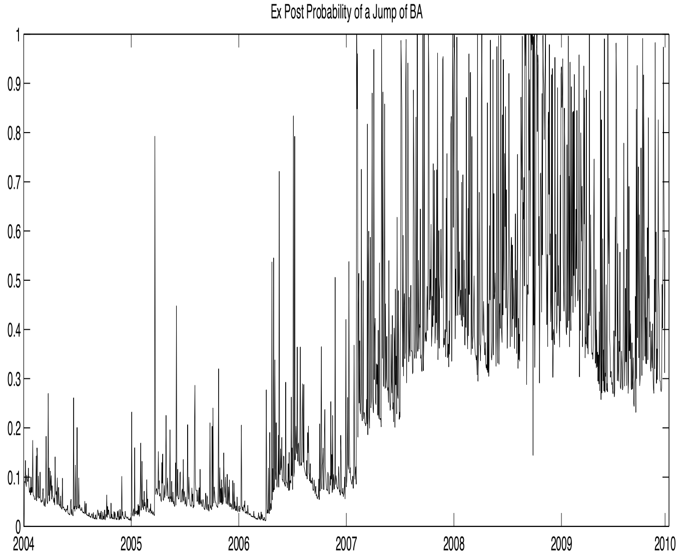


(c) JPM

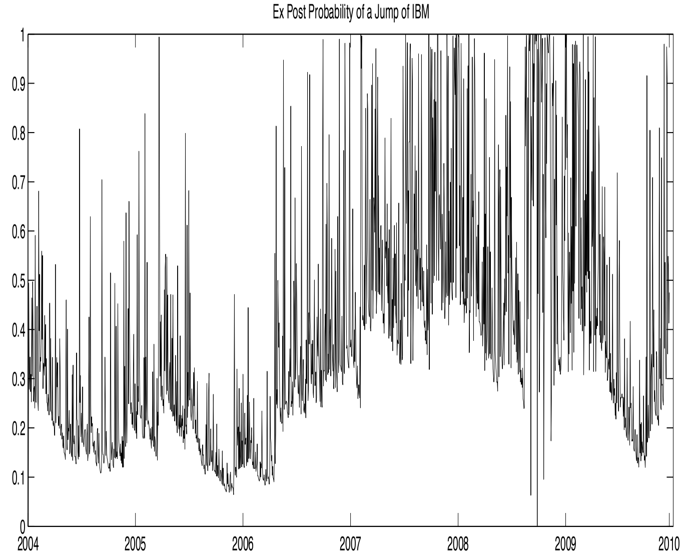


(d) UPS

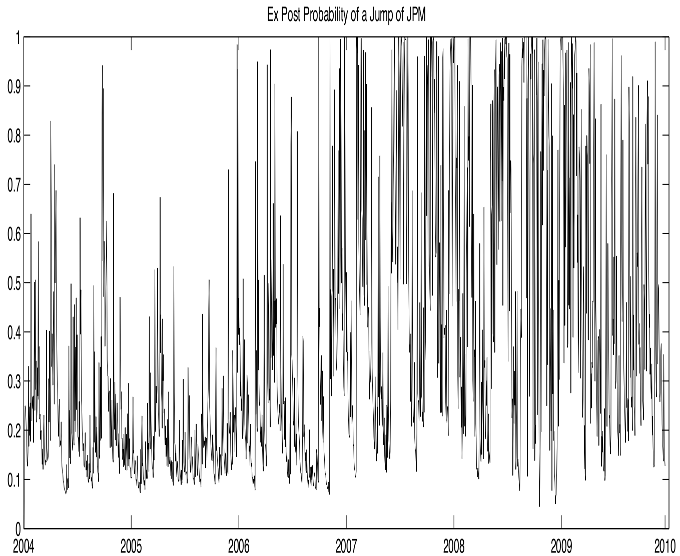
Figure 3: The expected number of jump arrivals, Λ_t^σ



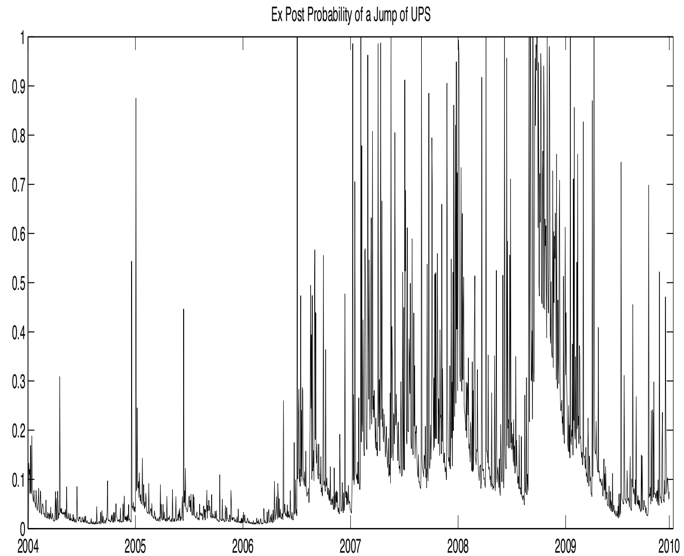
(a) BA



(b) IBM

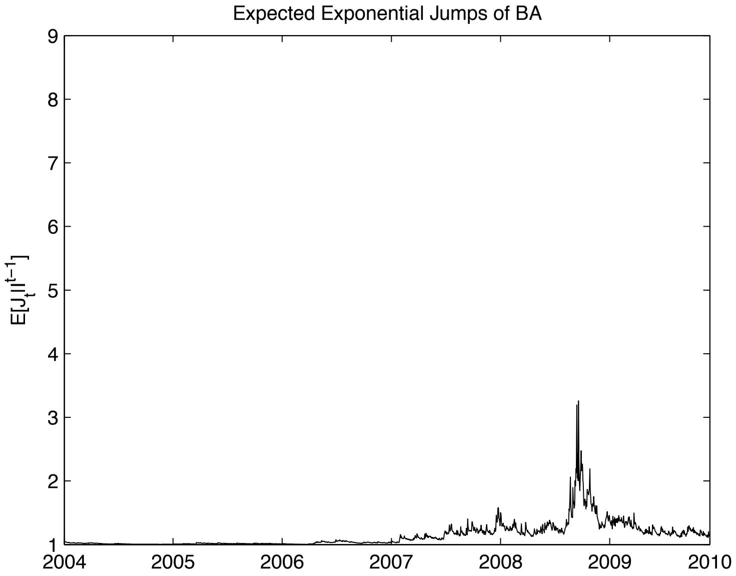


(c) JPM

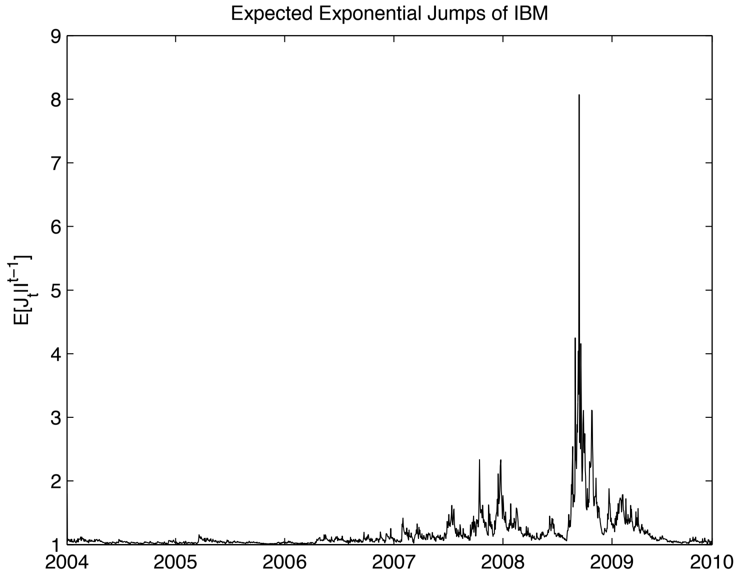


(d) UPS

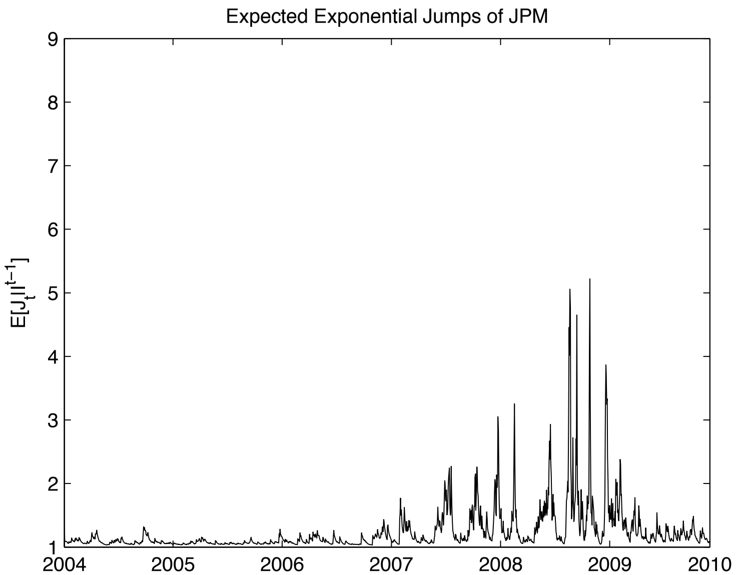
Figure 4: Ex-post probability of a jump, $P(N_{\sigma,t} \geq 1|I^t)$.



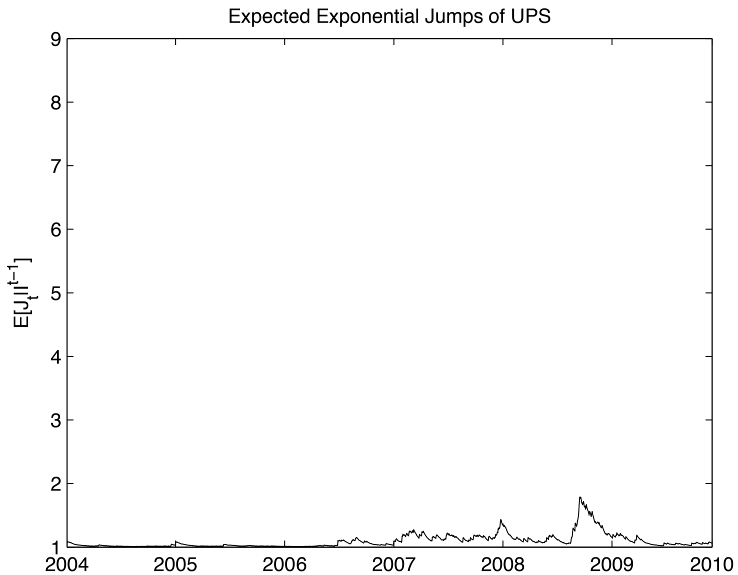
(a) BA



(b) IBM

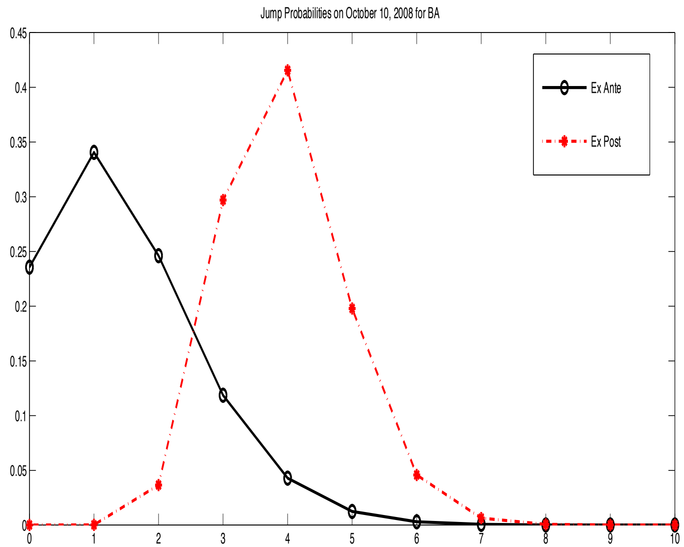


(c) JPM

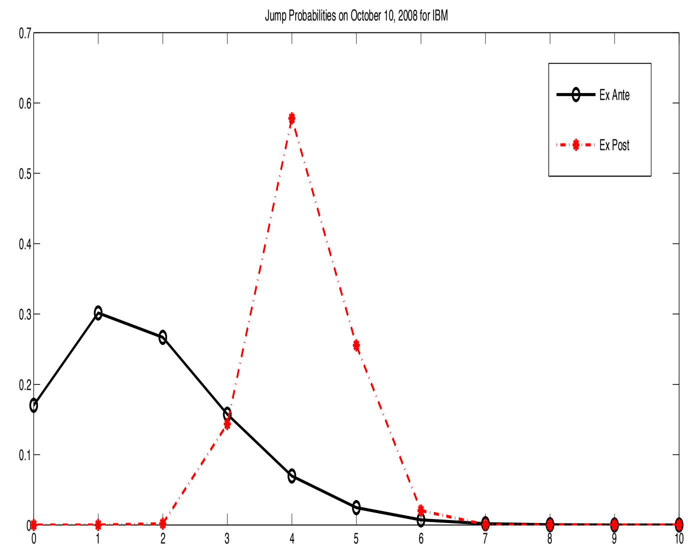


(d) UPS

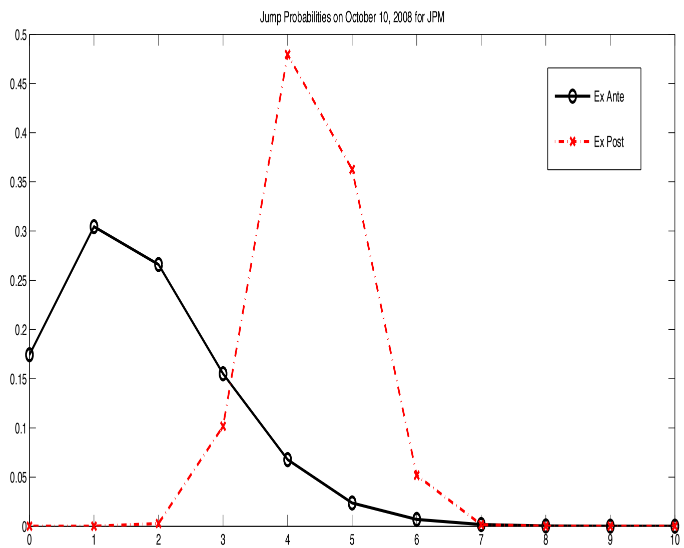
Figure 5: Estimated expected exponential jump, $\hat{J}_{t|t-1}$



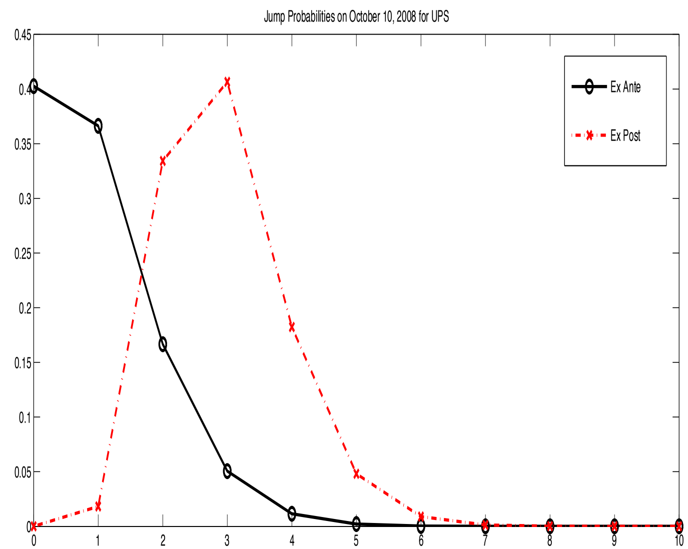
(a) BA



(b) IBM

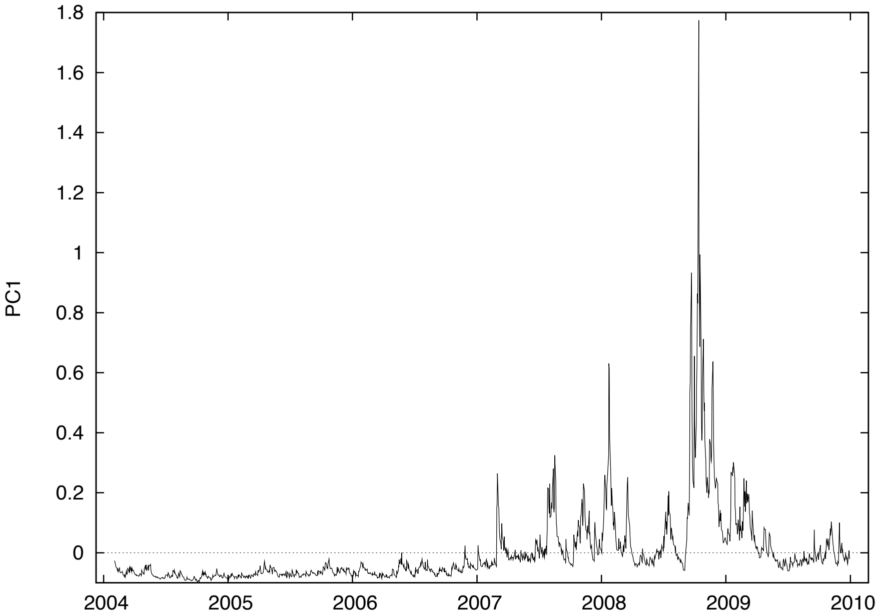


(c) JPM

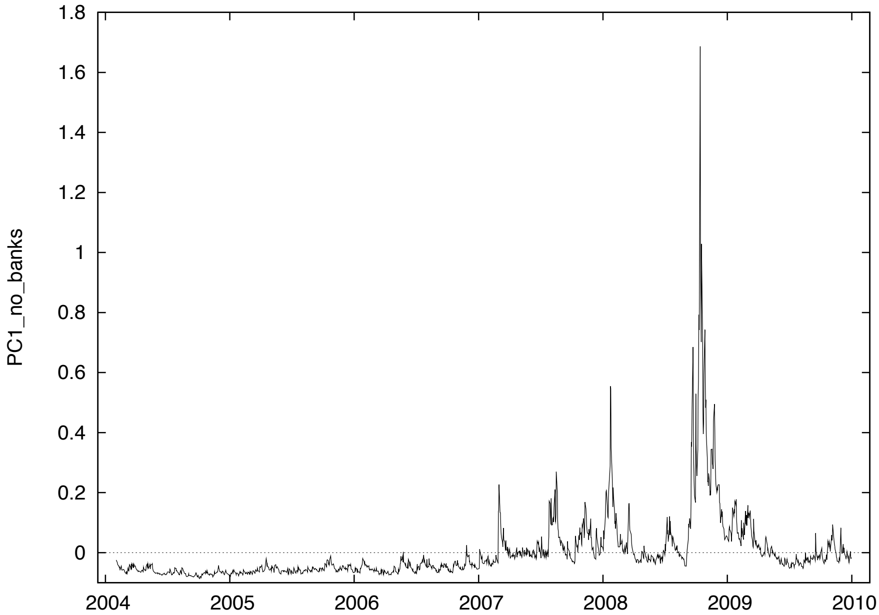


(d) UPS

Figure 6: Ex-ante and ex-post probability of jumps on October 10, 2008.



(a) Including the financial sector



(b) Excluding the financial sector

Figure 7: First principal component of estimated conditional jumps in daily volatilities.

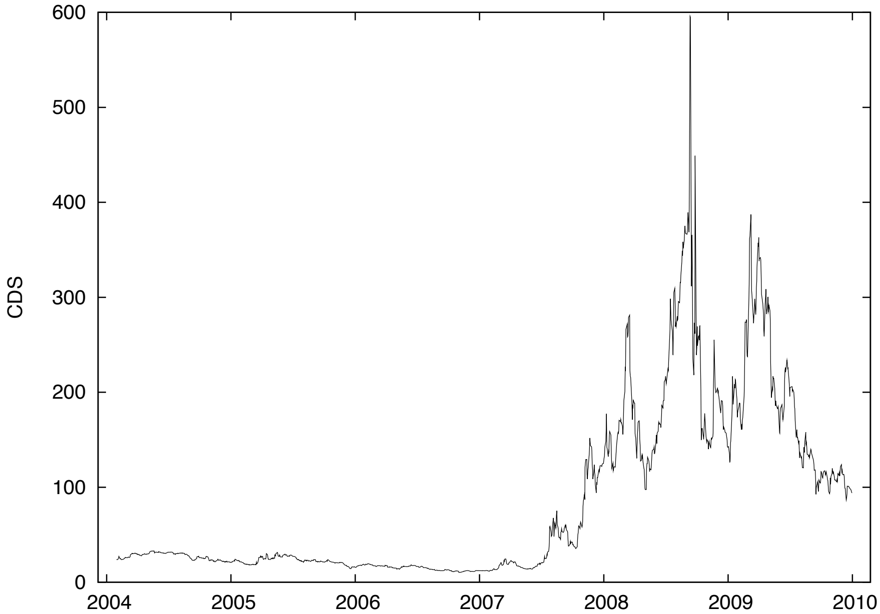


Figure 8: Credit default swap of US bank sector

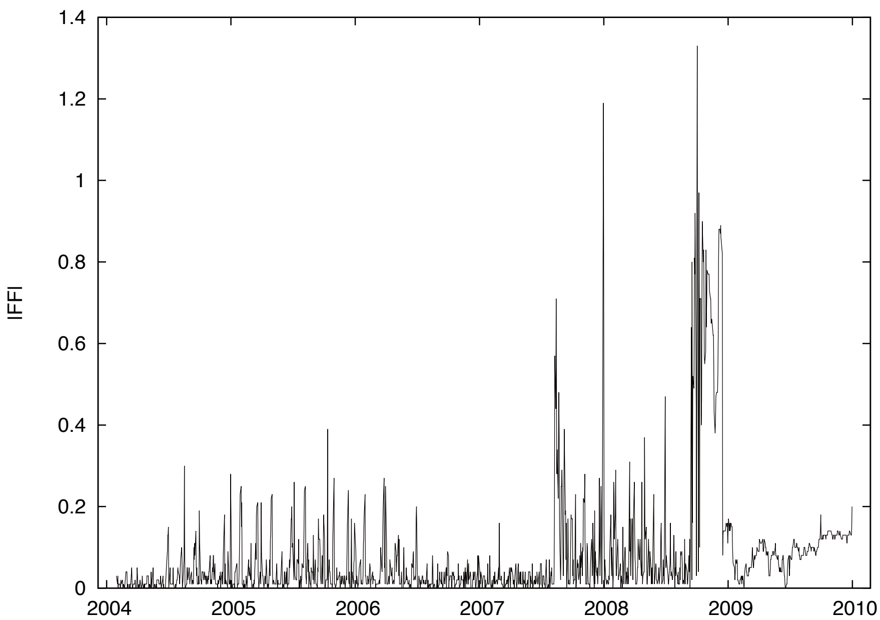


Figure 9: Absolute value of the difference between the effective and the target Federal Funds rates

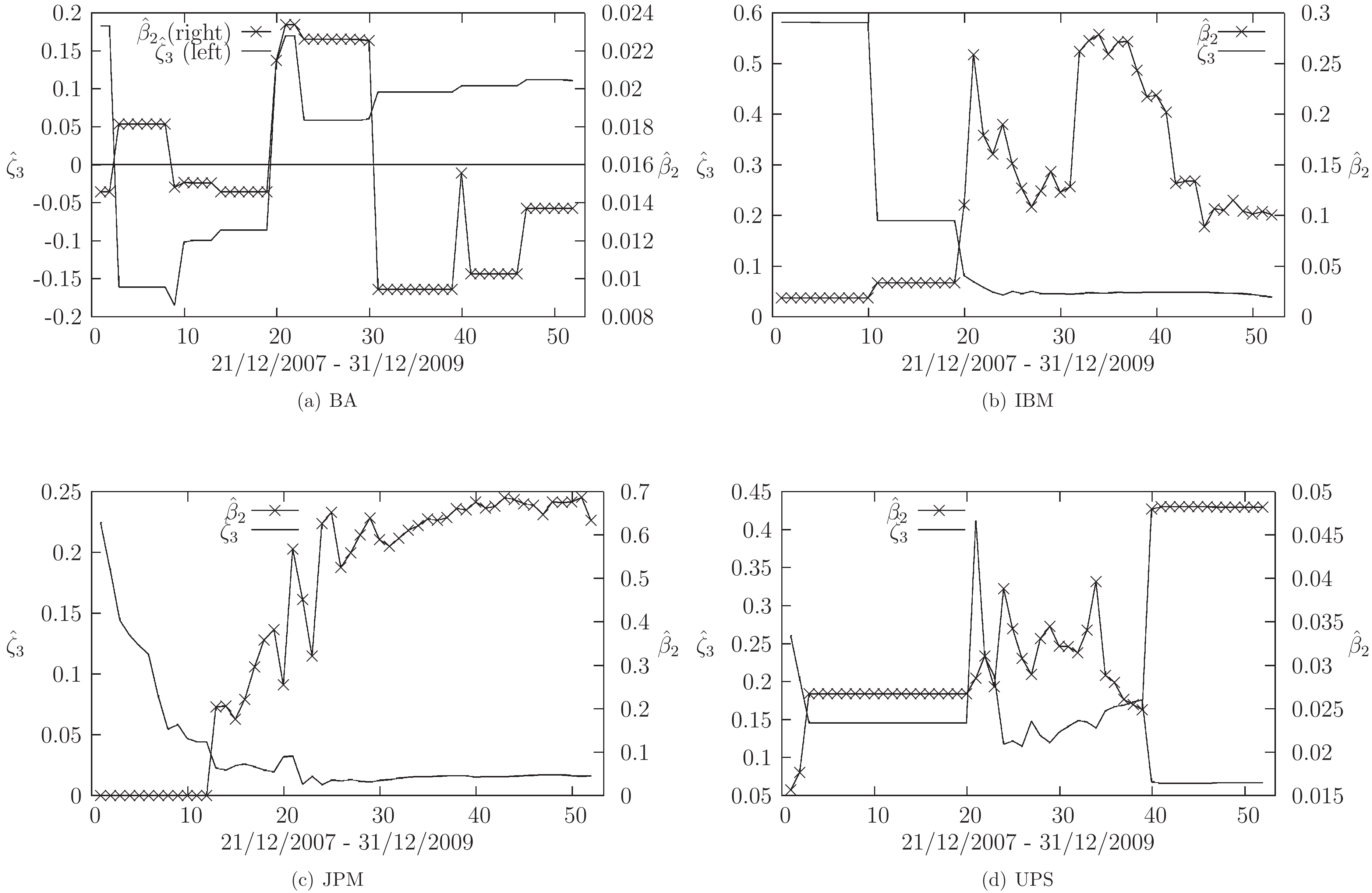
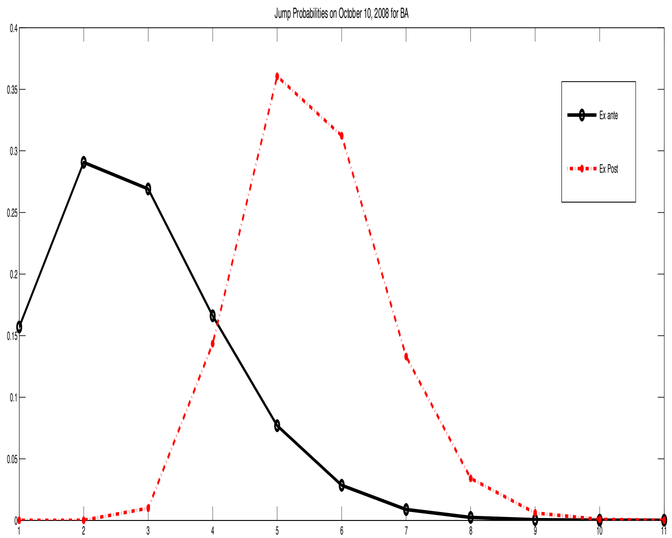
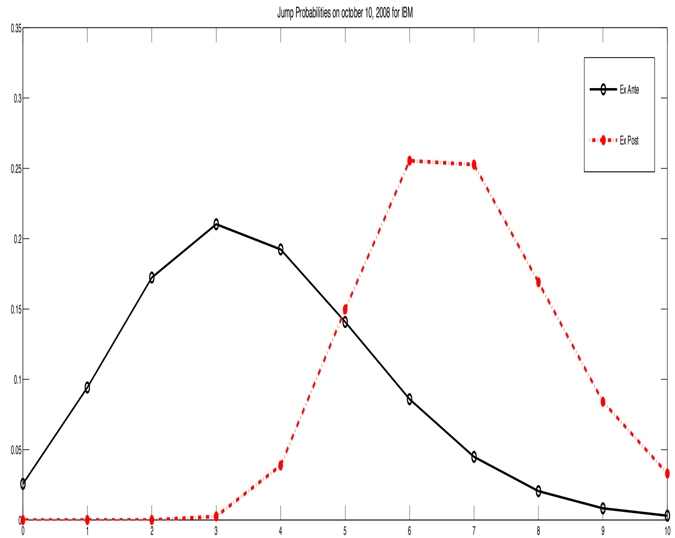


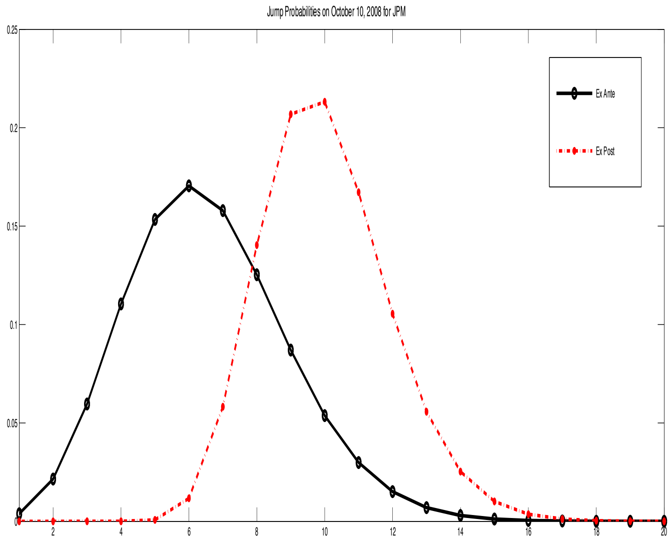
Figure 10: Rolling estimates of β_2 and ζ_3 in (17) and (18)



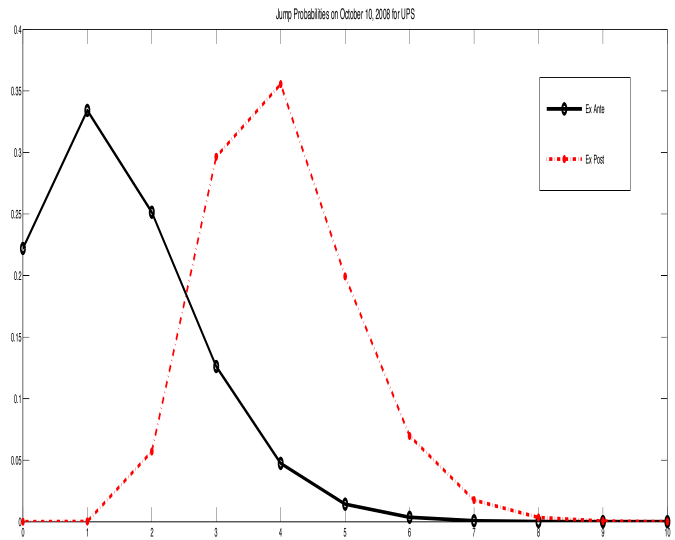
(a) BA



(b) IBM



(c) JPM



(d) UPS

Figure 11: Ex-ante and ex-post probability of jumps on October 10 2008, implied by the HAR-V-J model with CDS.