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Information Arrival, News Sentiment, Volatilities and Jumps of Intraday Returns

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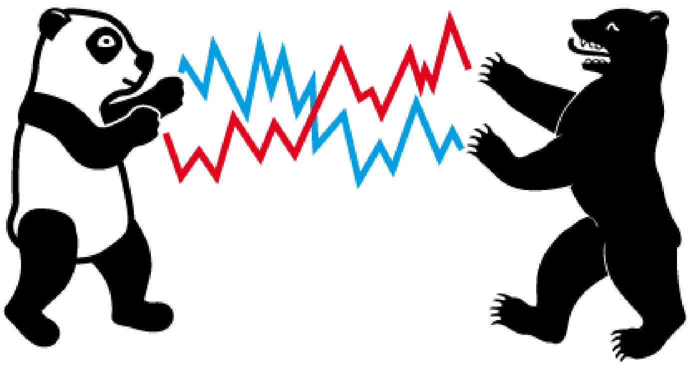

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Information Arrival, News Sentiment, Volatilities and Jumps of Intraday Returns *

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Abstract

This work aims to investigate the (inter)relations of information arrival, news sentiment, volatilities and jump dynamics of intraday returns. Two parametric GARCH-type jump models which explicitly incorporate both news arrival and news sentiment variables are proposed, among which one assumes news affecting financial markets through the jump component while the other postulating the GARCH component channel. In order to give the most-likely format of the interactions between news arrival and stock market behaviors, these two models are compared with several other easier versions of GARCH-type models based on the calibration results on DJIA 30 stocks. The necessity to include news processes in intraday stock volatility modeling is justified in our specific calibration samples (2008 and 2013, respectively). While it is not as profitable to model jump process separately as using simpler GARCH process with error distribution capable to capture fat tail behaviors of financial time series. In conclusion, our calibration results suggest GARCH-news

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model with skew-t innovation distribution as the best candidate for intraday returns of large stocks in US market, which means one can probably avoid the complicatedness of modelling jump behavior by using a simplier skew-t error distribution assumption instead, but it's necessary to incorporate news variables.

Keywords: information arrival, volatility modeling, jump, sentiment, GARCH

JEL classification: C52, C55, C58, G14

1 Introduction

Like the jargon 'location, location, location' in real estate industry, 'information, information, information' is the slogan when it comes to financial markets. The important role information plays in the formation of stock prices as well as in the price vibrations has been a keen topic ever since the latter half of last century. There are a plethora of research papers to investigate the (inter)relation between information arrival and stock price behaviors, among which two mainstreams evolved that are diverging on the modelling of information (news) processes. One stream models the information process as latent variable (Engle & Ng 1993, Maheu & McCurdy 2004), which is usually represented by the error term in widely-used ARCH-type volatility models (Engle 1982, Bollerslev 1986, Nelson 1991, Ding et al. 1993, Glosten et al. 1993). The other stream of literature describes information processes through explicit proxies, in either parametric or nonparametric settings, like volumes in Lamoureux & Lastrapes (1990), number of daily newspaper headlines and earnings announcements in Berry & Howe (1994), macroeconomic news in Ederington & Lee (1993) and Lahaye et al. (2011), macro and firm-specific announcements in Lee & Mykland (2008).

'Common knowledge' to practioners and researchers established that ARCH-type models well capture the stylized facts of financial markets, such as heteroskedasticity and volatility clustering. On the other hand, jump dynamics, which refer to discontinuties in price routes of financial assets, are also well documented (Merton (1976), Kou (2002), Pan

(2002), Yan (2011), Mehau et al. (2013), Ornthanalai (2014), Aït-Sahalia et al. (2015)). This dynamics, however, is less 'common' knowledge, and in particular, research on jump dynamics' (inter)relation with information arrival has not been widely addressed, although Merton made a strong argument in 1976 by saying that '"$\cdots$ the 'abnormal' vibrations in price are due to the arrival of important new information about the stock that has more than a marginal effect on price" and "Usually, such information will be specific to the firm and possibly its industry'. As far as we know, only Lamoureux & Lastrapes (1990), Lee & Mykland (2008), Boudt & Petitjean (2014) and Maheu & McCurdy (2004) provide some direct evidence on this topic, while at a later time, Bajgrowicz et al. (2015) argued that jump detected in high-frequency data are mostly spurious and vast majority of news do not cause jumps while in stead generate a market reaction in the form of bursts of volatility.

Even for the literature which supports the (inter)relation between news and jump risk, they have their own shortcomings. The first three use nonparametric methods to detect the high-frequency jumps of the financial markets and then match the jumps with high-frequency news data. Though as flexible as the methodologies are model-free, they face challenges of the accuracy in the detection test (Bajgrowicz et al. 2015) and the typical 'chicken-egg' problem: how to decide whether news lead jumps or the other way around. The last one from the paper list above models news via GARCH-jump process. However, the news variable in this model is assumed to be latent, which makes it very hard to exactly match and quantify the news effect. Therefore, in summary, the interactions between news and stock jumps still remain unclear.

It is hence necessary to investigate the (inter)relation of news arrival, news sentiment, stock volatilities and jump dynamics. In order to do so, we investigate a GARCH-jump-news model which explicitly lifts the news variables into the dynamic returns. Our approach has two comparative advantages: first, it avoids test accuracy problem and 'chicken-egg' problem by using a parametric setting; second, the explicit incorporation of high frequency news variables quantifies the news effect precisely. Our model is an extension of the model proposed by Maheu & McCurdy (2004) in terms of adding an additional assumption that news variables can either directly affect the GARCH component (GARCH channel) or the jump component (jump channel) of the intraday stock return process. Two variables are comprised as proxies for information arrival and information polarity for each stock: total number of relevant news in a certain time interval and the weighted sentiment of these news. These two variables are assumed to affect the return behavior contemporaneously. In a nutshell, we divide the return process into three parts, one determinstic long-run average return, one zero-mean EGARCH(1,1,1) process and one conditionally zero-mean jump component, which is assumed to be independent of the EGARCH(1,1,1) component. The modifications made in these two channels are listed respectively: (1)GARCH channel: GARCH component is affected additionally by the two news variables while the jump intensity remains as a simple autoregressive process as in Maheu & McCurdy (2004); (2) jump channel: the jump intensity are explicitly affected by the two news variables while GARCH component remains as in Maheu & McCurdy (2004). The two models will further be compared with normal error GARCH model (benchmark without news effect), normal error GARCH-news model (benchmark with news efect), skew-t error GARCH model (captures fat tails), skew-t error GARCH-news model (captures fat tails and explicitly models news effect) and GARCH-jump model(with jump but not explicit news). We calibrate these models on high frequency returns of DJIA 30 stocks in 2008 (crisis time) and 2013 (most recent time available from our database) and compare the model fitting based on maximum likelihood estimation. Stock data is obtained from TAQ database and news data from Thomson Reuters News Analytics. Both data is recorded to milliseconds. We resample these raw data into 15-minute frequency and then fit the aforementioned seven models. Empirical results show significant roles news variables play on volatilities or jump dynamics (the parameters are almost all significant at 5% significnce level). Besides, the inclusion of news variables improves model fitting (increased maximum likelihood values of models including news variables). While for jump dynamics, it's not as profitable as only considering simpler GARCH processes but with innovation distributions capable to capture fat tails. Comparison among seven models suggests GARCH-news with skew-t innovation distribution model the best candadiate for decribing high frequency returns of large US stocks.

The rest of the work is organized as follows: Section 2 introduces the GARCH-jump-news model which incorporates the news proxies into the dynamics of jump diffussion or GARCH component of return processes. Parameter calibration by maximum likelihood estimation is also presented in this section. Empirical results on DJIA 30 stocks are shown in Section 3. In this section we describe the data we use, the parameters estimation we achieve, the comparison among different models (including news proxies or not, including jump dynamics or not) in modelling the return and volatility of financial assets. Section 4 concludes the paper. Some important calibration results are left to Appendix and a lot others left out for space-saving purpose, which can be achieved on request.

2 GARCH-jump-news Model

2.1 Model specification

Our approach is based on Maheu & McCurdy (2004), but information proxies (relevant number as well as weighted sentiment of news) are added. Hence the news variables are explicit, i.e, opposite to a latent variable setting. We denote our model GARCH-jump-news model hereafter. Model specifications are slightly different under two different assumptions about the channels through which stock markets process information. However, the majority of these two specifications are the same, which includes the specification of intraday log-returns as in Equation (1)-(3):

$$r_t = \varepsilon_{1,t} + \varepsilon_{2,t} \tag{1}$$

$$\varepsilon_{1,t} = \sqrt{h_t} z_t, z_t \sim \mathrm{N}(0,1) \tag{2}$$

$$\varepsilon_{2,t} = J_t - \mathrm{E}[J_t|\Phi_{t-1}] = \sum_{k=1}^{n_t} Y_{t,k} - \theta\lambda_t, Y_{t,k} \sim \mathrm{N}(\theta, \delta^2) \tag{3}$$

More specificly, the log-returns can be decomposed into two components: GARCH innovation ($\varepsilon_{1,t}$) and jump innovation ($\varepsilon_{2,t}$) (it's reasonable to assume zero long-run deterministic mean since we use very high frequency data here). Based on past information $\Phi_{t-1} = \{r_{t-1}, r_{t-2}, \ldots, r_1\}$, $\varepsilon_{1,t}$, the zero-mean innovation with its variance following a EGARCH(1,1,1) process specified under jump channel as

$$\begin{aligned} \log(h_t) &= \omega + (\alpha + \alpha_j \operatorname{E}[n_{t-1}|\Phi_{t-1}])(|z_{t-1}| - \operatorname{E}|z_{t-1}|) \\ &+ (\alpha_a + \alpha_{a,j} \operatorname{E}[n_{t-1}|\Phi_{t-1}])z_{t-1} + \beta \log(h_{t-1}) \end{aligned} \tag{4}$$

where n_t is the number of jumps at time t. We consider EGARCH process here so as to incorporate the possible leverage effect (the negative correlation between the return and the volatility of a financial asset). Furthermore, the ex post assessment of the expected number of jumps ($\operatorname{E}[n_{t-1}|\Phi_{t-1}]$) also feeds back to the volatility of the GARCH component as in Equation (4). The jump innovation is specified to have conditional zero mean and arrival of jumps following a time-varying Poisson process with jump intensity λ_t:

$$\operatorname{P}(n_t = j|\Phi_{t-1}) = \frac{\exp(-\lambda_t)\lambda_t^j}{j!} \tag{5}$$

The time-varying jump intensity is affected by contemporaneous news proxies:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \eta_n N_t + \eta_s \log Sent_t \tag{6}$$

where N_t is the number of all relevant news at time t and $\log Sent_t = \log \frac{\sum_{i=1}^{k_t} rel_{it} neg_{it}}{\sum_{j=1}^{k_t} rel_{jt} pos_{jt}}$ with k_t the number of relevant news at time t, $rel_{it}, neg_{it}, pos_{it} \in [0,1]$ the score of relevance, positiveness and negativeness of the i_{th} news at time t for each specific stock. When there is no news for certain time intervals, we assign zero to both news variables. Both news variables here are assumed to be exogenous. For each jump, we take the jump size as generated by a normal distribution with mean θ and volatility δ, i.e. $Y_{i,k} \sim \operatorname{N}(\theta, \delta^2)$. While under GARCH channel, all definitions of variables are the same, the only differences are the formats of GARCH component and jump intensity, which are specified as follows:

$$\begin{aligned} \log(h_t) &= \omega + (\alpha + \alpha_j \operatorname{E}[n_{t-1}|\Phi_{t-1}])(|z_{t-1}| - \operatorname{E}|z_{t-1}|) \\ &+ (\alpha_a + \alpha_{a,j} \operatorname{E}[n_{t-1}|\Phi_{t-1}])z_{t-1} + \beta \log(h_{t-1}) + \eta_n N_t + \eta_s \log Sent_t \end{aligned} \tag{7}$$

Therefore, news variables are assumed to influence the intraday return behaviors through the GARCH component while the jump intensity are left to be driven by only its own past value and past values of jump residuals:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1} \tag{8}$$

The new variable ξ_t is a jump residual process, which is defined as $\xi_{t-1} = \mathrm{E}[n_{t-1}|\Phi_{t-1}] - \lambda_{t-1}$. $\mathrm{E}[n_{t-1}|\Phi_{t-1}]$ is ex post assessment of expected number of jumps that occured from $t-2$ to $t-1$. According to the definition of λ_{t-1}, we can understand ξ_{t-1} as the change in the conditional forecast of n_{t-1} when the information set is updated. Therefore, we decompose the jump intensity at time t into intensity at time $t-1$ based on information up to $t-2$ and conditional forecast using updated information until $t-1$.

To sum up, the GARCH-jump-news model through the jump channel is specified as in Equation (1)-(6), and the other through GARCH channel in Equation (1)-(3), (5) and (7)-(8).

Finally, under either specification, the two innovations are assumed to be contemporaneously independent of each other, which derives the total variance of log returns (under either channel) as the summation of the variance of the two innovations:

$$\mathrm{Var}(r_t|\Phi_{t-1}) = \mathrm{Var}(\varepsilon_{1,t}|\Phi_{t-1}) + \mathrm{Var}(\varepsilon_{2,t}|\Phi_{t-1}) = h_t + \lambda_t(\delta^2 + \theta^2) \tag{9}$$

This is going to be used in maximum likelihood estimation stated in Section 2.2.

2.2 Maximum likelihood estimation

Conditioning on j jumps occurring, the conditional density of returns is normal

$$f(r_t|n_t = j, \Phi_{t-1}) = \frac{1}{\sqrt{2\pi(h_t + j\delta^2)}} \exp\{-\frac{(r_t + \theta\lambda_t - \theta j)^2}{2(h_t + j\delta^2)}\} \tag{10}$$

Integrating out the number of jumps, we obtain the density of returns conditional on previous information

$$f(r_t|\Phi_{t-1}) = \sum_{j=0}^{\infty} f(r_t|n_t = j, \Phi_{t-1})\, \mathrm{P}(n_t = j|\Phi_{t-1}) \tag{11}$$

Then the ex post distribution of n_t jumps is calculated as

$$\mathrm{P}(n_t = j|\Phi_t) = \frac{f(r_t|n_t = j, \Phi_{t-1})\, \mathrm{P}(n_t = j|\Phi_{t-1})}{f(r_t|\Phi_{t-1})}, j = 0, 1, \ldots \tag{12}$$

In empirical work, we have to truncate the sum of infinity to some finite number, we simplify our model by considering either no jump or one jump here, we take it reasonable since high frequency data are used here to calibrate the model. Therefore, the truncation number we choose is 1.

$$f(r_t|\Phi_{t-1}) = f(r_t|n_t = j, \Phi_{t-1})\, \mathrm{P}(n_t = 0|\Phi_{t-1}) + f(r_t|n_t = j, \Phi_{t-1})\, \mathrm{P}(n_t = 1|\Phi_{t-1}) \tag{13}$$

Finally, maximize likelihood function is used to estimate the parameters vector
$\Gamma = (\omega, \alpha, \alpha_j, \alpha_a, \alpha_{aj}, \beta, \lambda_0, \rho, \eta_n, \eta_s, \theta, \delta)$ under jump channel or
$\Gamma = (\omega, \alpha, \alpha_j, \alpha_a, \alpha_{aj}, \beta, \eta_n, \eta_s, \lambda_0, \rho, \gamma, \theta, \delta)$ under GARCH channel

$$\begin{aligned} \Gamma &= \arg\max_{\Gamma} \sum_t \log\{f(r_t(\Gamma)|\Phi_{t-1})\} \\ &= \sum_t \log[\sum_{j=0}^{1} \frac{1}{\sqrt{2\pi(h_t + j\delta^2)}} \exp\{-\frac{(r_t + \theta\lambda_t - j\theta)^2}{2(h_t + j\delta^2)} - \lambda_t\} * \lambda_t^j/j!] \end{aligned} \tag{14}$$

2.3 Comparative Models

In this subsection we include five simpler versions of the model (GARCH with normal error, GARCH-news with normal error, GARCH with skew-t error, GARCH-news with skew-t error, GARCH-jump) as comparisons so as to decide whether it's better to account jumps and (or) news explicitly in high frequency stock return modelling. The specifications of models are briefly addressed here:

2.3.1 GARCH Model with normal error

$$r_t = \varepsilon_t \tag{15}$$

$$\varepsilon_t = \sqrt{h_t} z_t, z_t \sim \mathrm{N}(0,1) \tag{16}$$

$$\log(h_t) = \omega + \alpha(|z_{t-1}| - \mathrm{E}\,|z_{t-1}|) + \alpha_a z_{t-1} + \beta \log(h_{t-1}) \tag{17}$$

2.3.2 GARCH-news Model with normal error

$$r_t = \varepsilon_t \tag{18}$$

$$\varepsilon_t = \sqrt{h_t} z_t, z_t \sim \mathrm{N}(0,1) \tag{19}$$

$$\log(h_t) = \omega + \alpha(|z_{t-1}| - \mathrm{E}\,|z_{t-1}|) + \alpha_a z_{t-1} + \beta \log(h_{t-1}) + \eta_n N_t + \eta_s \log Sent_t \tag{20}$$

2.3.3 GARCH Model with skew-t error

$$r_t = \varepsilon_t \tag{21}$$

$$\varepsilon_t = \sqrt{h_t} z_t, z_t \sim \mathrm{skewt}(\nu, \lambda) \tag{22}$$

$$\log(h_t) = \omega + \alpha(|z_{t-1}| - \mathrm{E}\,|z_{t-1}|) + \alpha_a z_{t-1} + \beta \log(h_{t-1}) \tag{23}$$

2.3.4 GARCH-news Model with skew-t error

$$r_t = \varepsilon_t \tag{24}$$

$$\varepsilon_t = \sqrt{h_t} z_t, z_t \sim \mathrm{skewt}(\nu, \lambda) \tag{25}$$

$$\log(h_t) = \omega + \alpha(|z_{t-1}| - \mathrm{E}\,|z_{t-1}|) + \alpha_a z_{t-1} + \beta \log(h_{t-1}) + \eta_n N_t + \eta_s \log Sent_t \tag{26}$$

2.3.5 GARCH-jump Model

This simplification only differs from our model setting ((1)-(6)) by replacing (6) with (8), which means we don't consider news variables explicitly in the model, only jump component is included in this case.

3 Empirical Results

This part provides the calibration results of the afore-mentioned seven models on 15-min frequency DJIA 30 stock returns.

3.1 Data

The raw data we use in the empirical analysis is of ultra-high frequency. Both the stock prices from Trade & Quote (TAQ) database (obtained through Wharton Research Data Services) and news data from Thomson Reuters News Analytics (TRNA) are recorded to seconds or even milliseconds. We select the 30 constituents of Dow Jones Industrial Average (DJIA) index and the time period of Year 2008 and Year 2013. We choose Year 2008 because financial crisis probably generated more jumps than normal times. Then we compare the results of this year with that of 2013, the most recent data we could get from both databases, which, can also be regarded as one normal year. Then the comparison betweeen 2008 and 2013 can shed some light on whether economic conditions affect the (inter)relations between news arrivals and stock vibrations.

3.2 Parameter Estimation

We estimate the parameters of the seven models for 30 DJIA stocks log returns in 2008 and 2013 respectively. To save space, we only report the calibration results for Apple.Inc (AAPL) and JP Morgen Chase (JPM) in Table 2 and Table 3. Results for the rest 28 stocks can be achieved on request. As shown in the table, all parameters are significant at 5% significance level for AAPL and only news sentiment parameter is not significant in the case of JPM, in both 2008 and 2013. These are evidences showing the significant role news variables or jump innovations play in stock return processes. Furthermore, when news variables are included, parameter β, which measures the persistence of volatility, tends to decrease. The value of log likelihood suggests for these two stocks in both years, the best fitting model is the GARCH-news model with skew-t innovation, which means, although the jump-related parameters are all significant in GARCH-jump type models, if fat tails of return distribtions are accounted through skew-t distribution functions and news variables are included explicitly, it's not necessary to model the jump part separately for high frequency stock returns. Detailed tests on whether to include jump or news for all 30 stocks are presented in the following sections.

3.3 Model Comparison

Among these seven models, certain pairs are compared to investigate whether including news proxies or (and) jump component improve model fitting on intraday return data of US large stocks. We dissect this part into two main subsections: whether to include news proxies as in Section 3.3.1 and whether to include jump component in Section 3.3.2.

3.3.1 Including News?

Table 4 compares the results between GARCH model with normal error and GARCH-news model with normal error for the 30 stocks. Evidence shows for all stocks in 2008 and 2013, incorporating news variables in the modelling of GARCH effect improves the model fitting significantly (Likelihood ratio test rejects the null hypothesis which favors restricted model). The information arrival variable, which is measured as the number of relevant news in certain time intervals, are proved to be always positively related to the volatilities of intraday returns, news sentiment variable, on the other hand, plays a varying role in the volatility modeling for different stocks. In 2008, 9 stocks are positively related to news sentiment, 18 negatively related and 3 has insignificant relations. The result is quite similar in 2013 only with one more positive relations. Recall the definition of news sentiment as the logrithm of the weighted negativeness divided by the weighted positiveness of relevant news, the positive relation between stock return volatilities and news sentiment could then be interpreted as higher volatilities for negative news, keeping all other variables constant. Therefore, one third of the stocks add more evidence to the widely-acknowledged opinion that negative news should generate larger volatilities than positive one, while a little more than half others disapprove it. Even worse, half of this coefficient changes its sign from 2008 to 2013, which makes it rather difficult to reach any definite relation between the news sentiment and high frequency stock volatility.

Therefore, our calibration results on DJIA stocks cannot provide clear evidence for the relation between sentiment measure of news and stock volatilities. The reasons for it can be threefold: the sentiment effect is highly specific to individual stocks due to the uniqueness of each stock or market conditions can change the sentiment effect easily through some hidden scheme between the two or the news sentiment measures developed by Thomson Reuters is not advanced enough therefor the direct use of this measure leads to some confusing results. Further research which focuses on the topic of news sentiment effect on stock volatilities could probably control for stock individual characteristics or develop a market-switching model using longer data samples or use new machine learning methods to construct better sentiment measures. However, each of these would make our model much more complicated and hard to calibrate. Therefore, we will not go deeper in the current work.

The comparisons between GARCH model with skew-t error and GARCH-news model with skew-t error (Table 5), GARCH-jump model with GARCH-jump-news model under GARCH channel (Table 7) are quite similar. But the one with GARCH-jump model comparing with GARCH-jump-news model under jump channel (Table 6) is only rejected in 2 cases in 2008 and 18 in 2013. Therefore, including the news variables explicitly into the jump precess seems not so satisfying in our data sample. Apart from this model, we obtain the basic conclusions regrading to news inclusion in the modeling as follows: 1) news variables should be included to improve model fitting and 2)information arrivals always affect the return vibrations positively and 3) news sentiment still possesses indefinite significant effect on different stocks.

3.3.2 Including Jumps?

Table 8, Table 9 and Table 10 provide the sign of jump-related parameters for model GARCH-jump, GARCH-jump-news through jump channel and through GARCH channel, respectively. All the parameters are significant at 5% significance level and the feedbacks (a_j, $a_{a,j}$) that jump process generates on stock volatility is mostly positive, which is consistent with general understanding of financial market. λ_0, ρ, γ and δ are always positive governed by either its definition or the associated stochastic process. θ, the average jump size can either be positive or negative with a magnitude quite close to 0. Maximum likelihoods of of all seven models are presented in Table 11 and Table 12. When comparing the likelihood values of GJ v.s. GN, or GJNJ v.s. GNN, or GJNG v.s. GNN, for some stocks processes with jumps outperforms those without, but in almost equally many others, it is the other way around. Therefore whether to include jump component is stock-wise, in a certain sense.What's worse is that when GT and GNT are used as comparative models without considering jumps, they outperform the ones with jump modeling for all stocks. This outperformance comes from the skew-t component to reflect fatter tails of financial time series. Therefore, considering the 15-min high frequency data used in this paper, including jumps is actually not necessary and not as profitable as considering simpler GARCH processes with error distributions capable to capture the fat tail behaviours.

3.4 Best Model for DJIA Stocks

We summarize the best model out of the proposed seven for each DJIA stock in 2008 and 2013, respectively, in Table 11 and Table 12. For almost all the stocks in both years, the GARCH-news model with skew-t error distribution serves as the best candidate. Therefore, to model the behaviors of high frequency stock returns, it is wise and less time-consuming to leave the jump part alone and instead consider some distribution functions with fatter tails, like skew-t distribution. Although including jump components can improve model fitting compared to the classic GARCH model with normal error terms, we do not suggest doing so since we have better candidates with less complexity. In summary, the explicit incorporation of news is always profitable.

4 Conclusion

This research studies the (inter)relation among information arrival, news sentiment, stock volatilities and jump risks of stock markets through a parametric modelling of jump component and news variables into intraday return behaviors. High frequency stock price data as well as high frequency news data are extensively used to exactly match the news variables and stock return behaviors, which makes the explicit inclusion of news variables at high frequency level possible. Several GARCH type models are then compared in order to find out whether it is necessary to incorporate jump component and news variables into the modelling. Comparison between models with news variables and the corresponding ones without news variables leads to the conclusion that news variables yield a better model fitting, within which, news arrival is always positively related to stock volatility while news sentiment still has an indefinite but significant influence on volatilities. However, for the jump component, in our high frequency framework, it is not as profitable as considering simpler GARCH processes with error distributions capable to capture fat tail behaviors of financial returns, for instance, GARCH process with skew-t innovation distribution. Comparisons among all 7 models which are calibrated to DJIA 30 stocks in 2008 and 2013 suggests GARCH-news with skew-t error term as the best candidate for both years. Furthermore, since it's not the best to model jump component separately, the main conclusions for 2008 and 2013 are quite similar.

5 Appendix

5.1 Appendix A: Details about DJIA stocks

Symbol	Company	Exchange	Industry	Date Added
AAPL	Apple	NASDAQ	Consumer electronics	2015-03-19
AXP	American Express	NYSE	Consumer finance	1982-08-30
BA	Boeing	NYSE	Aerospace and defense	1987-03-12
CAT	Caterpillar	NYSE	Construction and mining equipment	1991-05-06
CSCO	Cisco Systems	NASDAQ	Conputer networking	2009-06-08
CVX	Chevron	NYSE	Oil & gas	2008-02-19
DD	DowDuPont	NYSE	Chemical industry	2017-09-01
DIS	Walt Disney	NYSE	Broadcasting and entertainment	1991-05-06
GE	General Electric	NYSE	Conglomerate	1907-11-07
GS	Goldman Sachs	NYSE	Banking, Financial services	2013-09-20
HD	The Home Depot	NYSE	Home improvement retailer	1999-11-01
IBM	International Business Machine	NYSE	Computers and technology	1979-06-29
INTC	Intel	NASDAQ	Semiconductors	1999-11-01
JNJ	Johnson & Johnson	NYSE	Pharmaceuticals	1997-03-17
JPM	JPMorgan Chase	NYSE	Banking	1991-05-06
KO	Cca-Cola	NYSE	Beverages	1987-03-12
MCD	McDonald's	NYSE	Fast food	1985-10-30
MMM	3M	NYSE	Conglomerate	1976-08-09
MRK	Merck	NYSE	Pharmaceuticals	1979-06-29
MSFT	Microsoft	NASDAQ	Software	1999-11-01
NKE	Nike	NYSE	Apparel	2013-09-20
PFE	Pfizer	NYSE	Pharmaceuticals	2004-04-08
PG	Procter & Gamble	NYSE	Consumer goods	1932-05-26
TRV	Travelers	NYSE	Insurance	2009-06-08
UNH	UnitedHealth Group	NYSE	Managed health care	2012-09-24
UTX	United Technologies	NYSE	Conglomerate	1939-03-14
V	Visa	NYSE	Consumer Banking	2013-09-20
VZ	Verizon	NYSE	Telecommunication	2004-04-08
WMT	Walmart	NYSE	Retail	1997-03-17
XOM	ExxonModil	NYSE	Oil & gas	1928-10-01

Table 1: Detail information of most current consituents of DJIA

5.2 Appendix B: Tables of the Empirical Results

para	GJNJ	GJNG	GN	GNN	GT	GNT	GJ
				2008			
ω	-10.7501	-7.7866	0.0078	-2.1791	-0.0570	-1.4418	-7.6536
α	0.2037	0.1964	0.0286	0.5481	0.0787	0.4449	0.2206
α_j	0.2373	0.2043					0.1712
α_a	-0.0391	0.00026	-0.0329	-0.0431	-0.0331	-0.0509	-0.1103
α_{aj}	-0.0598	0.0105					0.0398
β	0.0253	0.3021	0.9989	0.7920	0.9945	0.8642	0.3081
λ_0	0.631	0.0949					0.1091
ρ	-0.0154	0.3099					0.2381
γ		0.0807					0.1952
η_n	0.2483	0.1968		0.2055		0.1187	
η_s	-0.0351	0.0859		0.0336		0.0102	
θ	-0.0001	-0.0009					0.0002
δ	0.0184	0.0120					0.0170
LL	24526	24819	24197	24774	25120	25178	24501
				2013			
ω	-12.4387	-8.8891	-4.0784	-5.6851	-3.0815	-4.3835	-8.7640
α	0.0562	0.0328	0.6133	0.3231	0.3536	0.3820	0.0281
α_j	0.0666	0.0802					0.0537
α_a	0.0129	0.0370	-0.2251	-0.0331	-0.0618	-0.0316	0.0007
α_{aj}	0.0007	-0.0082					0.0152
β	0.0285	0.3161	0.6320	0.5437	0.7478	0.6523	0.3014
λ_0	0.0709	0.1138					0.0920
ρ	-0.0442	0.3059					0.3030
γ		0.0967					0.2006
η_n	0.0465	0.1788		0.2036		0.1543	
η_s	-0.0315	0.0923		0.0347		0.0256	
θ	0.0005	0.0003					0.0002
δ	0.0092	0.0043					0.0096
LL	30312	30635	28309	30375	30453	30855	30165

Table 2: Parameter estimations of AAPL for 2008 (upper panel) and 2013 (lower panel)- GJNJ, GJNG, GN, GNN, GT, GNT, GJ stand for model GARCH-jump-news under jump channel, GARCH-jump-news under GARCH channel, GARCH with normal error, GARCH-news with normal error, GARCH with skew-t error, GARCH-news with skew-t error and GARCH-jump respectively, insignificant parameters (5% significance level) are reported in red

para	GJNJ	GJNG	GN	GNN	GT	GNT	GJ
				2008			
ω	-5.4291	-5.5060	-0.0151	-1.7891	0.0577	-1.1994	-5.2758
α	0.1764	0.2165	0.0814	0.4612	0.1141	0.4262	0.2137
α_j	0.1276	0.2107					0.1680
α_a	0.0164	0.0200	-0.0061	0.0176	-0.0160	0.0243	-0.0114
α_{aj}	0.0457	0.0139					0.0006
β	0.4881	0.4936	0.9976	0.8214	0.9939	0.8824	0.5073
λ_0	0.0605	0.0954					0.0539
ρ	0.5239	0.5114					0.4926
γ		0.1087					0.1515
η_n	0.0549	0.2038		0.0930		0.0479	
η_s	-0.0395	-0.0461		0.0286		-0.0071	
θ	0.0011	0.0009					0.0026
δ	0.0159	0.031					0.0205
LL	23015	23238	22835	23000	23533	23605	23129
				2013			
ω	-12.8466	-9.0220	-4.3583	-5.7129	-2.7187	-4.4859	-9.0078
α	0.0737	0.0755	0.3707	0.3802	0.3407	0.3920	0.0211
α_j	0.1126	0.0768					0.0823
α_a	-0.0499	-0.0099	-0.0237	-0.0534	-0.0128	-0.0349	0.0391
α_{aj}	0.0284	-0.0065					-0.0051
β	-0.0002	0.3142	0.6372	0.5505	0.7823	0.6499	0.3205
λ_0	0.2180	0.1064					0.1077
ρ	0.0102	0.2934					0.2928
γ		0.0953					0.1997
η_n	0.1476	0.1411		0.2424		0.1825	
η_s	-0.0372	0.1033		0.0009		0.0024	
θ	-0.0002	0.0000					-0.0001
δ	0.0039	0.0038					0.0052
LL	31155	31601	30505	31407	31522	31795	31372

Table 3: Parameter estimations of JPM for 2008 (upper panel) and 2013 (lower panel)- GJNJ, GJNG, GN, GNN, GT, GNT, GJ stand for model GARCH-jump-news under jump channel, GARCH-jump-news under GARCH channel, GARCH with normal error, GARCH-news with normal error, GARCH with skew-t error, GARCH-news with skew-t error and GARCH-jump respectively, insignificant parameters (5% significance level) are reported in red

stock	2008 significant η_n	2008 significant η_s	2008 LR test	2013 significant η_n	2013 significant η_s	2013 LR test
AAPL	+	+	✓	+	+	✓
AXP	+	-	✓	+	-	✓
BA	+	+	✓	+	+	✓
CAT	+		✓	+	-	✓
CSCO	+	-	✓	+	-	✓
CVX	+	-	✓	+	+	✓
DD	+	-	✓	+	-	✓
DIS	+	-	✓	+	-	✓
GE	+		✓	+	-	✓
GS	+	+	✓	+		✓
HD	+	+	✓	+	-	✓
IBM	+	-	✓	+	-	✓
INTC	+	-	✓	+	-	✓
JNJ	+	-	✓	+	-	✓
JPM	+	+	✓	+		✓
KO	+		✓	+	-	✓
MCD	+	-	✓	+	+	✓
MMM	+	-	✓	+	-	✓
MRK	+	+	✓	+	-	✓
MSFT	+	-	✓	+	+	✓
NKE	+	-	✓	+	+	✓
PFE	+	-	✓	+	+	✓
PG	+	-	✓	+	-	✓
TRV	+	-	✓	+	+	✓
UNH	+	-	✓	+	-	✓
UTX	+	+	✓	+	-	✓
V	+	-	✓	+	-	✓
VZ	+	+	✓	+	-	✓
WMT	+	+	✓	+	+	✓
XOM	+	-	✓	+	+	✓
sum	30(+)	9(+) 18(-)	30(✓)	30(+)	10(+) 18(-)	30(✓)

Table 4: Significance of news variables and likelihood ratio test of DJIA stocks - GN v.s. GNN

stock	2008 significant η_n	2008 significant η_s	2008 LR test	2013 significant η_n	2013 significant η_s	2013 LR test
AAPL	+	+	✓	+	+	✓
AXP	+	+	✓	+	-	✓
BA	+	+	✓	+	+	✓
CAT	+	-	✓			✓
CSCO	+	-	✓	+	-	✓
CVX	+	-	✓	+	-	✓
DD	+	-	✓	+	-	✓
DIS	+	-	✓	+	-	✓
GE	+	-	✓	+	-	✓
GS	+	-	✓	+	+	✓
HD	+	-	✓	+	-	✓
IBM	+	-		+	-	✓
INTC	+		✓	+	-	✓
JNJ	+	-	✓	+	-	✓
JPM	+	-	✓	+	+	✓
KO	+	-	✓	+	-	✓
MCD	+	+	✓	+	-	✓
MMM	+	-	✓	+	-	✓
MRK	+	-	✓	+	-	✓
MSFT	+	-	✓	+	+	✓
NKE	+	-	✓			✓
PFE	+	-	✓	+	+	✓
PG	+	-	✓	+	-	✓
TRV	+	-	✓	+	-	✓
UNH	+	-	✓	+	-	✓
UTX		-	✓	+	-	✓
V	+	-	✓	+	-	✓
VZ	+	+	✓	+	-	✓
WMT	+	+	✓	+	+	✓
XOM	+	-	✓	+	+	✓
sum	29(+)	6(+) 23(-)	29(✓)	28(+)	8(+) 20(-)	30(✓)

Table 5: Significance of news variables and likelihood ratio test of DJIA stocks - GT v.s. GNT

stock	2008 significant η_n	2008 significant η_s	2008 LR test	2013 significant η_n	2013 significant η_s	2013 LR test
AAPL	+	-	✓	+	-	✓
AXP	+			-	-	✓
BA	+	-		+	-	✓
CAT	+	-		+	+	
CSCO	+	-		+	-	✓
CVX	+	-		+	-	✓
DD	+	-		+	-	✓
DIS	+	-		+	-	✓
GE	+	-		+	-	✓
GS	+	-	✓	+	-	✓
HD	+	-		+	-	✓
IBM	+	-		+	-	✓
INTC	+	-		+	-	✓
JNJ	+	-		+	+	✓
JPM	+	-		+	-	
KO	+	-		+	-	
MCD	+			-	-	
MMM	+	-		+	-	
MRK	+	+		+	-	✓
MSFT	+	-		+	-	
NKE	+	-		+	-	
PFE	+	-		+	-	
PG	+	-		+	-	✓
TRV	+	-		+	-	
UNH	+	-		+	-	
UTX	+	-		+	-	
V	+	-		+	-	✓
VZ	+	-		+	-	
WMT	+	-		+	-	✓
XOM	+	+		+	-	✓
sum	30(+)	2(+) 28(-)	2(✓)	30(+)	2(+) 28(-)	18(✓)

Table 6: Significance of news variables and likelihood ratio test of DJIA stocks - GJ v.s. GJNJ

	2008			2013		
stock	significant η_n	significant η_s	LR test	significant η_n	significant η_s	LR test
AAPL	+	+	✓	+	+	✓
AXP	+	+	✓	+	-	
BA	+	+	✓	+	-	✓
CAT	+	-	✓	+	+	✓
CSCO	+	-	✓	+	-	✓
CVX	+	+	✓	+	-	✓
DD	+	-	✓	+	-	✓
DIS	+	+	✓	+	-	✓
GE	+	+	✓	+	+	✓
GS	+	+	✓	+	+	✓
HD	+	+	✓	+	-	✓
IBM	+	-	✓	+	-	✓
INTC	+	-	✓	+	-	✓
JNJ	+	-	✓	+	-	✓
JPM	+	-	✓	+	+	✓
KO	+	-	✓	+	-	✓
MCD	+	-	✓	+	-	
MMM	+	-	✓	+	-	✓
MRK	+	+	✓	+	+	✓
MSFT	+	-	✓	+	+	✓
NKE	+	-	✓	+	-	✓
PFE	+	+	✓	+	+	✓
PG	+	-	✓	+	-	✓
TRV	+	+		+	+	✓
UNH	+	-	✓	+	-	✓
UTX	+	-	✓	+	-	✓
V	+	-		+	-	✓
VZ	+	-	✓	+	+	✓
WMT	+	-	✓	+	+	✓
XOM	+	+	✓	-		✓
sum	30(+)	12(+) 18(-)	28(✓)	30(+)	11(+) 19(-)	28(✓)

Table 7: Significance of news variables and likelihood ratio test of DJIA stocks - GJ v.s. GJNG

	2008							2013						
stock	a_j	$a_{a,j}$	λ_0	ρ	γ	θ	δ	a_j	$a_{a,j}$	λ_0	ρ	γ	θ	δ
AAPL	+	+	+	+	+	-	+	+	+	+	+	+	+	+
AXP	+	+	+	+	+	-	+	+	-	+	+	+	-	+
BA	+	-	+	+	+	+	+	+	+	+	+	+	-	+
CAT	+	+	+	+	+	+	+	+	+	+	+	+	-	+
CSCO	+	+	+	+	+	+	+	+	+	+	+	+	+	+
CVX	+	-	+	+	+	-	+	+	-	+	+	+	-	+
DD	+	+	+	+	+	+	+	+	-	+	+	+	-	+
DIS	+	+	+	+	+	+	+	+	+	+	+	+	-	+
GE	+	-	+	+	+	+	+	+	+	+	+	+	+	+
GS	+	+	+	+	+	-	+	+	-	+	+	+	+	+
HD	+	-	+	+	+	+	+	+	-	+	+	+	+	+
IBM	+	-	+	+	+	-	+	+	-	+	+	+	-	+
INTC	+	-	+	+	+	-	+	+	+	+	+	+	-	+
JNJ	+	+	+	+	+	+	+	+	-	+	+	+	-	+
JPM	+	-	+	+	+	+	+	+	-	+	+	+	-	+
KO	+	+	+	+	+	+	+	+	-	+	+	+	-	+
MCD	+	-	+	+	+	-	+	+	-	+	+	+	-	+
MMM	+	-	+	+	+	-	+	+	-	+	+	+	-	+
MRK	+	-	+	+	+	-	+	+	-	+	+	+	-	+
MSFT	+	+	+	+	+	-	+	+	+	+	+	+	-	+
NKE	+	+	+	+	+	-	+	+	+	+	+	+	-	+
PFE	+	+	+	+	+	-	+	+	+	+	+	+	+	+
PG	+	+	+	+	+	-	+	+	-	+	+	+	-	+
TRV	+	-	+	+	+	+	+	+	+	+	+	+	-	+
UNH	+	+	+	+	+	+	+	-	+	+	+	+	+	+
UTX	+	+	+	+	+	+	+	+	-	+	+	+	+	+
V	+	+	+	+	+	+	+	+	+	+	+	+	+	+
VZ	+	+	+	+	+	+	+	+	+	+	+	+	-	+
WMT	+	+	+	+	+	-	+	-	+	+	+	+	-	+
XOM	+	-	+	+	+	+	+	+	+	+	+	+	-	+

Table 8: Significance of jump parameters- GJ model

	2008						2013					
stock	a_j	$a_{a,j}$	λ_0	ρ	θ	δ	a_j	$a_{a,j}$	λ_0	ρ	θ	δ
AAPL	+	-	+	-	-	+	+	+	+	-	+	+
AXP	+	+	+	+	+	+	+	-	+	-	-	+
BA	+	+	+	+	-	+	+	-	+	+	-	+
CAT	+	+	+	+	+	+	+	+	+	+	-	+
CSCO	+	-	+	+	+	+	+	+	+	+	-	+
CVX	+	+	+	+	-	+	+	+	+	-	-	+
DD	+	+	+	+	+	+	+	-	+	+	+	+
DIS	+	-	+	+	+	+	+	+	+	-	-	+
GE	+	+	+	+	-	+	+	-	+	+	-	+
GS	+	+	+	+	+	+	+	-	+	-	-	+
HD	+	-	+	-	+	+	+	+	+	+	+	+
IBM	+	+	+	-	-	+	+	+	+	+	+	+
INTC	+	+	+	+	+	+	+	+	+	-	+	+
JNJ	+	+	+	-	-	+	+	-	+	-	-	+
JPM	+	+	+	+	+	+	+	+	+	+	-	+
KO	+	-	+	+	+	+	+	-	+	-	-	+
MCD	+	+	+	+	-	+	-	+	+	+	-	+
MMM	+	+	+	-	-	+	+	+	+	+	-	+
MRK	+	-	+	+	+	+	+	+	+	+	-	+
MSFT	+	+	+	-	-	+	+	+	+	+	-	+
NKE	+	-	+	+	+	+	+	+	+	-	-	+
PFE	+	+	+	+	+	+	+	+	+	+	-	+
PG	+	+	+	+	+	+	+	-	+	+	-	+
TRV	+	+	+	+	+	+	+	+	+	+	-	+
UNH	+	+	+	+	-	+	+	+	+	+	-	+
UTX	+	-	+	+	+	+	+	+	+	-	-	+
V	+	+	+	+	-	+	+	+	+	-	-	+
VZ	+	+	+	+	+	+	+	+	+	+	+	+
WMT	+	+	+	+	-	+	+	+	+	-	+	+
XOM	+	-	+	+	-	+	+	+	+	-	-	+

Table 9: Significance of jump parameters - GJNJ model

	2008							2013						
stock	a_j	$a_{a,j}$	λ_0	ρ	γ	θ	δ	a_j	$a_{a,j}$	λ_0	ρ	γ	θ	δ
AAPL	+	+	+	+	+	-	+	+	-	+	+	+	+	+
AXP	+	+	+	+	+	+	+	+	-	+	+	+	-	+
BA	+	-	+	+	+	+	+	-	-	+	+	+	+	+
CAT	+	-	+	+	+	-	+	+	+	+	+	+	+	+
CSCO	+	+	+	+	+	+	+	+	+	+	+	+	-	+
CVX	+	+	+	+	+	+	+	+	-	+	+	+	-	+
DD	+	+	+	+	+	+	+	+	-	+	+	+	-	+
DIS	+	-	+	+	+	+	+	-	+	+	+	+	-	+
GE	+	+	+	+	+	+	+	+	-	+	+	+	+	+
GS	+	+	+	+	+	-	+	+	-	+	+	+	+	+
HD	+	+	+	+	+	+	+	+	+	+	+	+	-	+
IBM	+	+	+	+	+	-	+	-	-	+	+	+	-	+
INTC	+	+	+	+	+	-	+	+	-	+	+	+	+	+
JNJ	+	+	+	+	+	+	+	+	+	+	+	+	+	+
JPM	+	+	+	+	+	+	+	+	-	+	+	+	-	+
KO	+	-	+	+	+	-	+	+	+	+	+	+	-	+
MCD	+	+	+	+	+	+	+	+	+	+	+	+	-	+
MMM	+	-	+	+	+	+	+	+	-	+	+	+	-	+
MRK	+	+	+	+	+	-	+	+	+	+	+	+	-	+
MSFT	+	+	+	+	+	+	+	+	+	+	+	+	+	+
NKE	+	+	+	+	+	+	+	+	-	+	+	+	-	+
PFE	+	+	+	+	+	+	+	+	-	+	+	+	+	+
PG	+	-	+	+	+	+	+	+	+	+	+	+	-	+
TRV	+	-	+	+	+	-	+	+	-	+	+	+	-	+
UNH	+	+	+	+	+	-	+	+	+	+	+	+	-	+
UTX	+	-	+	+	+	-	+	+	-	+	+	+	+	+
V	+	-	+	+	+	-	+	+	-	+	+	+	+	+
VZ	+	+	+	+	+	+	+	+	+	+	+	+	-	+
WMT	+	+	+	+	+	+	+	+	-	+	+	+	-	+
XOM	+	+	+	+	+	+	+	+	+	+	+	+	-	+

Table 10: Significance of jump parameters- GJNG model

model	GJNJ	GJNG	GN	GNN	GT	GNT	GJ
AAPL	24526	24819	24197	24774	25120	25178	24501
AXP	23304	23578	22965	23206	23870	23888	23459
BA	26302	26586	25803	26289	27014	27081	26451
CAT	25457	25699	25477	25549	26240	26248	25661
CSCO	25663	25861	25499	25765	26171	26196	25675
CVX	25960	26208	26306	26347	26829	26838	26132
DD	26139	26383	25960	26309	26828	26847	26211
DIS	26528	26729	26626	26731	27306	27326	26653
GE	25750	26209	25250	26153	26772	26813	25943
GS	23320	23717	23530	23716	24227	24244	23168
HD	24726	24923	24430	24483	25171	25184	24793
IBM	27137	27400	27257	27374	27907	27909	27189
INTC	25752	25969	25356	25779	26213	26259	25792
JNJ	29936	30359	30305	30575	31027	31093	30208
JPM	23015	23238	22835	23000	23533	23605	23129
KO	28722	28977	28254	28697	29439	29455	28849
MCD	27531	27769	27295	27673	28179	28220	27583
MMM	27636	27775	27693	27740	28274	28287	27726
MRK	26216	26644	24854	26206	26847	26974	26355
MSFT	26650	26958	26430	26897	27169	27316	26768
NKE	26030	26188	25585	25966	26564	26572	26088
PFE	27635	27887	27658	27799	28387	28439	27769
PG	29031	29329	29050	29197	29842	29860	29157
TRV	25174	25311	25193	25297	25858	25906	25392
UNH	24898	25200	24011	25752	25636	25751	25068
UTX	27029	27270	26844	26929	27758	27776	27194
V	25899	26029	25969	30274	31640	31684	26171
VZ	26244	26591	25899	26376	26730	26928	26373
WMT	27680	27921	27543	27747	28271	28330	27767
XOM	26333	26606	26637	26663	27185	27193	26439

Table 11: Best model fitting for DJIA stocks in 2008

model	GJNJ	GJNG	GN	GNN	GT	GNT	GJ
AAPL	30312	30635	28309	30375	30453	30853	30165
AXP	32419	32402	30959	31719	32464	32609	32417
BA	31837	31804	29805	31647	31871	32303	31782
CAT	32053	32264	30765	31663	32253	32428	32107
CSCO	31124	31403	28117	31040	31373	31633	31051
CVX	33229	33571	32655	33131	33540	33692	32879
DD	32471	32609	31531	31963	32633	32735	32462
DIS	32296	32330	31209	31928	32339	32487	32225
GE	32540	32821	31280	32522	32733	32975	32500
GS	30840	30854	29802	30777	30920	31201	30754
HD	32106	32143	31105	31648	32234	32347	32079
IBM	33252	33033	31523	33196	33423	33680	32985
INTC	31359	31567	30181	31266	31545	31743	31325
JNJ	33882	34026	33093	33690	34028	34200	33817
JPM	31155	31601	30505	31407	31522	31795	31372
KO	32910	33057	31906	32530	33126	33255	32995
MCD	34345	34411	32977	33738	34534	34698	34418
MMM	33800	34030	32671	33335	34039	34144	33830
MRK	32305	32490	31614	32395	32590	32809	32295
MSFT	31347	31644	29293	31522	31613	32005	31245
NKE	31771	31955	30039	31599	32051	32206	31810
PFE	32174	32352	31410	32197	32390	32604	32226
PG	33180	33380	31730	33051	33389	33574	33193
TRV	33495	33592	32147	32849	33601	33677	33426
UNH	31567	31762	30190	31322	31770	31933	31567
UTX	32824	32975	31919	32365	33048	33196	32969
V	31748	31770	30589	31420	31958	32099	31763
VZ	32356	32468	31057	32216	32486	32721	32237
WMT	33467	33859	32533	33532	33815	34026	33637
XOM	33643	33773	32671	33543	33665	33897	33539

Table 12: Best model fitting for DJIA stocks in 2013

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