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The Twitter myth revisited: Intraday investor sentiment, Twitter activity and individual-level stock return volatility

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ABSTRACT

Taking an intraday perspective, we study the dynamics of individual-level stock return volatility, measured by absolute 5-minute returns, and Twitter sentiment and activity. After accounting for the intraday periodicity in absolute returns, we discover some statistically significant co-movements of intraday volatility and information from stock-related Tweets for all constituents of the Dow Jones Industrial Average. However, economically, the effects are of negligible magnitude and out-of-sample forecast performance is not improved when including Twitter sentiment and activity as exogenous variables. From a practical point of view, we find that high-frequency Twitter information is not particularly useful for highly active investors with access to such data for intraday volatility assessment and forecasting when considering individual-level stocks.

1. Introduction

With the ever increasing speed of trading in recent years, intraday volatility assessment and forecasting have gained importance for highly active investors such as derivative traders and hedge funds. Intraday volatility measures are important input factors in high-frequency risk management applications, for the calculation of time-varying liquidity measures, and to concert limit order placement strategies or the optimal scheduling of trades (e.g., Engle and Sokalska, 2012; Giot, 2005). However, not only has the speed of trading increased rapidly, but also the way investors can comment or share their opinion about company and stock market performances on social media platforms.

A growing body of behavioral finance literature links investor sentiment, derived from social media, to financial markets (for a recent survey, see Bukovina, 2016). While institutional investors have the means to monitor actively traded stocks constantly, social media represents one channel through which retail investors can easily access stock market relevant information (e.g., Chen et al., 2014). Stock prices, reflecting the trading activities of both institutional and retail investors, might reflect retail investor trading activities that are, at least partially, influenced by sentiment. Let us view the average highly active investor as a professional or institutional investor, close to the definition of an informed investor. By contrast, individual or retail investors are often thought of as having psychological biases and are seen as noise traders in the way portrayed by Kyle (1985) or Black (1986). While professional investors are seen as rational investors, they can still base decisions on less rational factors such as investor sentiment. Early research on investor sentiment has proposed that such rational investors could bet against sentiment driven noise traders to make a profit, albeit with caution to the costs and risks that such strategies would entail (e.g., De Long et al., 1990; Shleifer and Vishny, 1997). Thus, given that retail investors have been shown to trade excessively in attention-grabbing stocks (Barber and Odean, 2007) and to trade in concert (e.g., Kumar and Lee, 2006; Barber et al., 2009), one might think that professional investors could exploit the behavior of retail investors, who use social media platforms as investment forums to obtain information about securities' potential performance.

Recently, the social media platform Twitter has been used to extract a proxy for investor sentiment. For instance, Bollen et al. (2011) derive six social mood dimensions from Twitter messages (Tweets). Their results indicate that predictions of the Dow Jones Industrial Average (DJIA) are improved through the inclusion of some of these social mood dimensions. Sprenger et al. (2014a) derive good and bad news from more than 400,000 Tweets related to the S&P 500 and find that these news have an impact on the market. In addition, Sprenger et al. (2014b) discover a relationship between stock related Twitter sentiment and returns, volume of Tweets and trading volume of the respective stock, as well as disagreement

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and return volatility. Looking at the transmission and aggregation of information, they also demonstrate that providing above average investment advice is associated with more quotes and an increase in followers. Along this line, Yang et al. (2015) unravel the existence of a financial community on Twitter and find that the weighted sentiment of its most influential contributors has significant predictive power for market movement. While Sprenger et al. (2014b) focus on some well-known companies from the S&P 100, other studies from the behavioral finance literature look at stock market indices only. Moreover, all studies mentioned above focus on daily stock market and social media data.

Taking an intraday perspective and considering individual-level stocks, this paper has two main objectives: (i) assessing the impact of Twitter investor sentiment and Twitter activity on return volatility and (ii) testing the performance of intraday volatility forecasts augmented with this additional information. Following, among others, Andersen and Bollerslev (1997) and Bollerslev et al. (2000), we use high-frequency absolute 5-minute returns as a measure for volatility, since these display greater dynamics, i.e. more persistent autocorrelation patterns and thus conform better to the long-memory property of stock return volatility, than squared returns (for a discussion of this finding see, for example, Ding et al., 1993; Forsberg and Ghysels, 2007). Twitter sentiment and activity, the latter measured as the number of Tweets in a certain time interval, are available to investors through commercial data providers. By assuming the role of a professional investor with access to such data, we obtain intraday prices, Twitter sentiment and the number of Tweets (henceforth Twitter count) at 1-minute frequency for all constituents of the DJIA and a time period from June 18, 2015 to December 29, 2017 from Bloomberg. We focus on blue-chip stocks such as the DJIA constituents, since other securities are not equally well covered in terms of Twitter sentiment and activity, rendering an intraday analysis infeasible. Before conducting any meaningful time series analysis and intraday volatility forecasting, we address the well-documented intraday periodicity in absolute 5-minute returns within the framework of a two-step estimation procedure involving a Fourier flexible form (FFF) estimation (for example, see Andersen and Bollerslev, 1997; Bollerslev et al., 2000). This approach is readily applied to the intraday absolute returns of the DJIA constituents. In order to examine the dynamics between Twitter sentiment, activity and return volatility, the filtered absolute 5-minute returns obtained from this estimation procedure are then used in a bivariate vector-autoregressive (VAR) model together with average 5-minute Twitter sentiment and 5-minute Twitter count, respectively. Finally, we adapt the heteroscedastic autoregressive (HAR) model of Corsi (2009) to the intraday context and use a panel HAR to forecast filtered absolute 5-minute returns for individual-level stocks. While we observe some statistically significant feedback effects between intraday volatility and Twitter sentiment as well as Twitter count for many stocks, the performance of the panel HAR model, augmented with exogenous information from Twitter, is mixed among the sample of stocks considered in this paper. In general, estimated coefficients are small in magnitude and gains in out-of-sample forecasting performance, if present at all, are negligible in every single case. Thus, professional investors do not benefit from augmenting forecasts with such Twitter data when considering individual-level stocks and an intraday setting. Our results, obtained from the sample of 30 DJIA constituents, clearly differ from research that considers aggregated data in the form of stock market indices and daily observations of index returns and social media sentiment or activity. Gains of using high-frequency financial and social media data are limited, rendering the discussion more interesting for the case of observations at lower frequencies. Moreover, one could say that our results are in line with the notion of professional investors as stated above: the performance of liquid blue-chip stocks should be determined by information that is related to securities' fundamentals and not by investor sentiment obtained from social media platforms. The majority of such stocks are held by institutional investors and thus should be priced more efficiently (e.g., Boehmer and Kelley, 2009).

Our paper is structured as follows: Section 2 describes the absolute return time series data and shortly outlines the two-step estimation procedure used to account for the deterministic intraday periodicity that is present in intraday absolute returns. Section 3 describes the Twitter data in more detail and assesses the interactions between intraday Twitter sentiment, Twitter count and intraday filtered absolute returns in a bivariate VAR framework. Forecasting of intraday volatility, using exogenous information in the form of Twitter sentiment and Twitter count in a panel HAR setting, is the objective of Section 4. Lastly, Section 5 concludes.

2. Intraday periodicity and long-memory volatility

2.1. Data

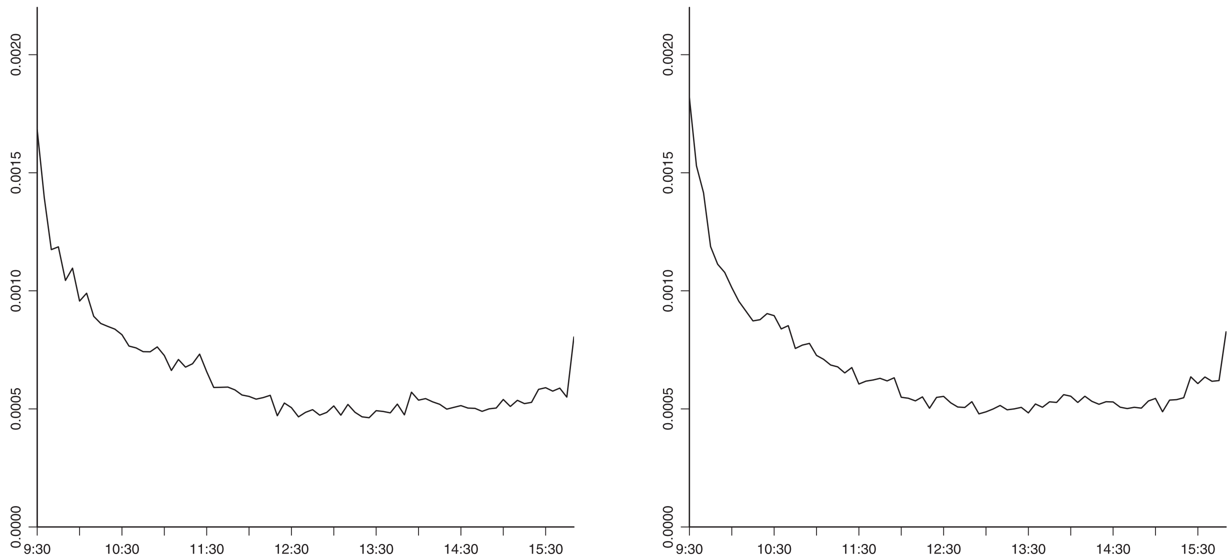
Intraday prices for all DJIA constituents at 1-minute frequency are obtained from Bloomberg and cover the period from June 18, 2015 to December 29, 2017. For each trading day and stock up to 390 prices are obtained, corresponding to the regular trading hours from 0930 to 1600 EST. Continuously compounded returns are calculated as the log-price changes from one minute to the next. Accordingly, 5-minute returns are calculated as the sum of five 1-minute returns. Excluding overnight returns, this leaves 77 intraday 5-minute returns for each trading day and stock. Occasionally, it is the case that there is no trading recorded by Bloomberg over a given 5-minute time interval, leading to missing values. However, these cases are not frequent and missing values should not distort our empirical results. With a total of 639 trading days, each consisting of 77 intraday 5-minute returns, this leaves us with a total of 49,203 observations. Thus, for all DJIA constituents denote the series of 5-minute returns as $R_{t,\,n}$, where $t = 1, 2, \ldots, 639$ and $n = 1, 2, \ldots, 77$. Another time series that is used in the two-step estimation procedure to get rid of the pronounced intraday periodicity in absolute returns, explained in more detail below, consists of daily closing prices ranging from January 04, 2010 to December 29, 2017. Analogously, daily returns are calculated as the log-price changes between two consecutive days.

2.2. Intraday periodicity in absolute returns

When analyzing 5-minute absolute returns, a clear pattern emerges that has been documented in the literature by, among others, Andersen and Bollerslev (1997, 1998); Andersen et al. (2000) and Bollerslev et al. (2000): while the volatility process shows clear conditional heteroscedasticity and long-memory properties on a daily basis, one can observe a strong deterministic intraday periodicity.

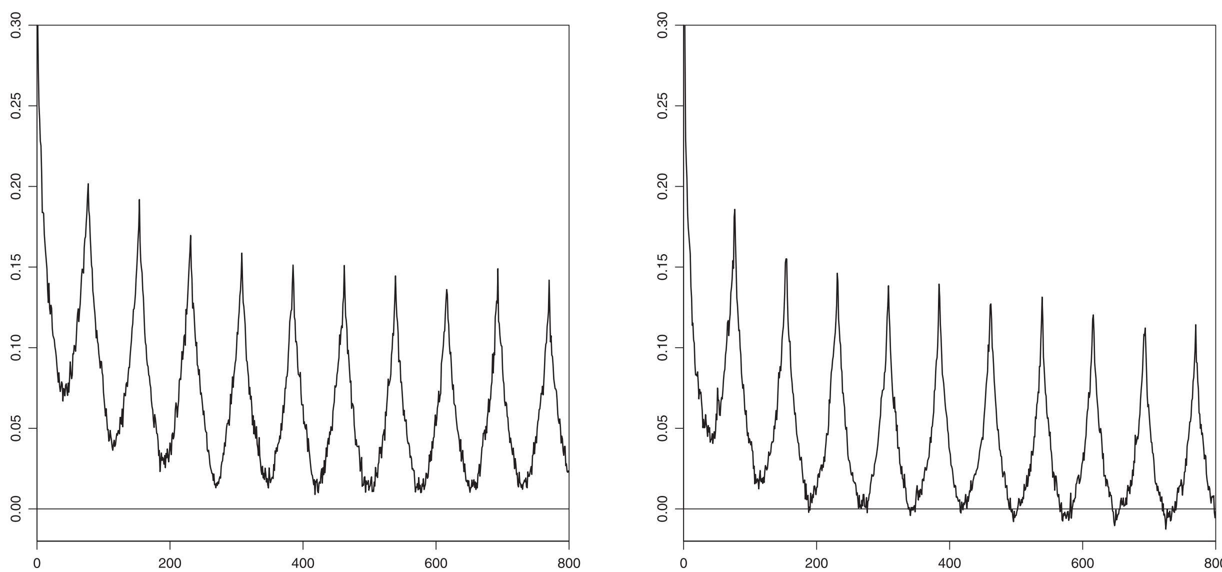
The intraday periodicity is illustrated in Fig. 1, where the average intraday absolute 5-minute return is calculated over the cross-section of each of the n intraday bins. Thus, absolute 5-minute returns are plotted for the "average" trading day. In the following, results are shown for the stocks of two companies, International Business Machines Corporation (IBM) and Walmart Inc. (WMT), but results are similar for all remaining constituents of the DJIA and are available upon request.[1] Fig. 1 reveals a pronounced difference in the volatility over the trading day. For both stocks one can see

[1] These two stocks are chosen since they display both significant Twitter sentiment and Twitter count terms in all models that we entertain in our empirical analysis. Table A.1 in the appendix provides an overview over all stocks.



(a) IBM (b) WMT

Fig. 1. Average of absolute 5-minute returns The plots show the average of intraday absolute 5-minute returns calculated for two stocks, (a) IBM and (b) WMT.



(a) IBM (b) WMT

Fig. 2. ACFs of absolute 5-minute returns The plots show ACFs of intraday absolute 5-minute returns over 800 5-minute lags, which correspond to approximately ten trading days, for two stocks, (a) IBM and (b) WMT.

that volatility is high at the beginning of the trading day, decreases throughout the day with its minimum around lunch hours, and increases again slightly at the end of the trading day. Several early papers have attributed the pronounced U-shape pattern in intraday stock market volatility to the strategic interaction of traders around market openings and closures (for example, see Admati and Pfleiderer, 1988; 1989). Interestingly, in the case of individual-level stock absolute 5-minute returns, this "U" shape rather resembles an inverted "J" shape, since, on average, volatility right after the market opening dwarfs volatility at the market closing.

Moreover, this deterministic intraday periodicity induces a certain pattern in the autocorrelation functions (ACFs) of absolute 5-minute returns, which is visible in Fig. 2. Here, ACFs are plotted over ten trading days. However, the given pattern is consistent over the whole sample period. On the one hand, one can observe the above mentioned long-memory properties of absolute 5-minute returns, since the ACFs decay slowly and are statistically significant over a long time horizon. On the other hand, a clear repetitive pattern can be seen. The deterministic intraday periodicity induces a distorted U-shape in the sample autocorrelations, each of these lasting exactly for one trading day.

Previous research has shown that in order to conduct meaningful time series analysis and to derive intraday forecasts of 5-minute absolute returns, one has to take both of these patterns into account. One way to purge the intraday absolute 5-minute returns of the periodic component is by applying a two-step procedure based on an FFF estimation (Gallant, 1981). The approach outlined in the following has first been introduced by Andersen and Bollerslev (1997) and is easily applied to individual-level stock absolute return time series. The next section provides a short description of this estimation procedure, while a longer and more technical description can be found in Appendix A.1.

2.3. Two-step estimation procedure

To model the periodic intraday volatility component in high-frequency absolute returns, we follow Andersen and Bollerslev (1997) and decompose 5-minute returns as:

$$R_{t,n} - \mathbb{E}(R_{t,n}) = \varepsilon_{t,n} = s_{t,n}\sigma_{t,n}Z_{t,n} \tag{1}$$

where $\sigma_{t,\,n}$ denotes a 5-minute volatility factor for trading day t and $Z_{t,\,n}$ is an i.i.d. zero mean and unit variance innovation. The periodic component, $s_{t,\,n}$, is estimated in a two-step estimation procedure that involves an FFF regression, which is illustrated in more detail in Appendix A.1. In order to obtain $\sigma_{t,\,n}$, σ_t is estimated using the longer sample of daily returns from January 4, 2010 until December 29, 2017. The sample is chosen such that there is a larger number of observations available for estimation but it excludes the financial crisis. We use an asymmetric power ARCH (A-PARCH) to capture the daily volatility clustering. The A-PARCH of Ding et al. (1993) does not only allow for a leverage effect in the volatility equation, but also accounts for the empirical finding that the sample autocorrelation of absolute returns is usually larger than that of squared returns. Ding et al. (1993) show empirically that the A-PARCH is able to capture the long-memory properties of daily absolute returns. The 5-minute volatility factor for trading day t, $\sigma_{t,\,n}$, is then simply estimated by $\hat{\sigma}_{t,n} = \hat{\sigma}_t / N^{1/2}$, where N is the number of observations per trading day.

The second step involves estimating the parameters of the FFF specification by OLS. Estimation is based on the whole sample of intraday 5-minute returns, instead of simply estimating the average periodic pattern across the trading day. This two-step procedure is not fully efficient. However, Andersen and Bollerslev (1998) show that, in general, the parameter estimates are consistent, given the FFF regression is correctly specified in the second step.

While the actual parameter estimates are difficult to interpret, one can plot the average estimated intraday periodic volatility factor together with the average absolute 5-minute returns in order to see whether or not the estimate provides a sufficient approximation of the intraday shape of average returns. This is depicted in Fig. 3. The average periodic component seems to approximate the distinct shape of absolute returns quite well and thus the two-step estimation procedure does seem to be a reasonable approach in our case.

However, while the A-PARCH estimate, $\hat{\sigma}_t$, may successfully capture the volatility clustering in the daily returns, it might not be a good model for $\hat{\sigma}_{t,n}$. Following, for example, Bollerslev et al. (2000) the estimated seasonal component in the 5-minute absolute returns is filtered away to see whether or not the chosen approach is valid empirically. Denote the raw absolute 5-minute returns by $|R_{t,\,n}|$, the filtered 5-minute absolute returns are then given by:

$$R^*_{t,n} = \frac{|R_{t,n}|}{\hat{s}_{t,n}} \tag{2}$$

where $\hat{s}_{t,n}$ denotes the normalized estimate for the periodic component, as obtained from the two-step estimation procedure. In accordance with Andersen and Bollerslev (1997), the autocorrelogram of the filtered absolute returns should exhibit a strictly positive and slowly declining autocorrelation. This would indicate that the long-memory properties are the characteristic attribute of the return volatility process, after the deterministic intraday component is removed. As can be seen from Fig. 4, this is exactly the case for the two chosen stocks.

The ACFs of the filtered absolute 5-minute returns seem way smoother than the ACFs of the raw absolute 5-minute returns with their distinct U-shaped pattern, exhibiting a strictly positive and slowly declining correlogram. Again, results are similar across all constituents of the DJIA.

3. Twitter sentiment and Twitter count effects

3.1. Data

In addition to the return time series, intraday Twitter sentiment and count data for all DJIA constituents at a 1-minute frequency are obtained from Bloomberg for June 18, 2015 through December 29, 2017. While Twitter count measures the overall activity, i.e. the number of Tweets for a given stock and minute, Twitter sentiment ranges continuously from 1 (positive investor sentiment) to −1 (negative investor sentiment). Both measures are based on an undisclosed algorithm used by Bloomberg. Dealing with Twitter count data from Bloomberg is straightforward: in our data set we code Twitter count as zero for a given stock in minutes without any Twitter activity and record the number of Tweets in minutes where Bloomberg registers some Twitter activity. Twitter sentiment is calculated by Bloomberg every minute for all stocks using the last 30 minutes of available data on positively and negatively associated Tweets. However, only if the absolute difference between the newly calculated sentiment value and the previous value is larger than 0.005, Bloomberg updates Twitter sentiment for the respective stock. Accordingly, in our data set we only update the value for Twitter sentiment if for a given stock and minute a change in sentiment is observed in the data obtained from Bloomberg. If there is no observed change in sentiment for a given stock and minute, we instead fill in such missing values with the previously observed change in Twitter sentiment on a given trading day. Let us be more precise and use an example to illustrate how we deal with this issue in our data: if the first observed sentiment value for a given stock is at 1021 EST and the second one at 1043 EST on a given trading day, then all values until 1021 EST are missing values in our data set for this stock and trading day; the first non-missing value is at 1021 EST and all values between 1021 EST and 1043 EST are equal to the sentiment observed at 1021 EST, only at 1043 EST do we again record a change in investor sentiment. Thus, we assume that investor sentiment, as obtained from Twitter, remains constant for time periods where Bloomberg does not register a change in Twitter sentiment larger than 0.005 in absolute value. Lastly, in order to match the 5-minute intraday frequency of the return data, time series of 5-minute Twitter sentiment are obtained as the average sentiment over five minutes for each stock, whereas time series of Twitter count constitute the absolute number of counts over each 5-minute time interval for each stock.

The upper panels of Fig. 5 illustrate the time series of Twitter sentiment for the stocks of IBM and WMT, the two lower panels show the respective ACFs over ten trading days. While the sentiment time series for WMT has a higher variability compared to IBM's sentiment time series, both display long-memory dependencies in their ACFs. The effect of past sentiment or count values on the present remains significant for more than three trading days for both stocks, with significant lags even after nine trading days for WMT. Similarly, for Twitter count the upper panels of Fig. 6 illustrate the respective time series for IBM and WMT, whereas the two lower panels depict their ACFs. One can see that at most times the number of Tweets for WMT exceeds the number of Tweets for IBM. However, for both stocks the Twitter count time series appears to possess long-memory properties. Compared to Twitter sentiment, the memory of the Twitter count time series for IBM seems to be longer, as Plot (c) of Fig. 5 shows significant lags even

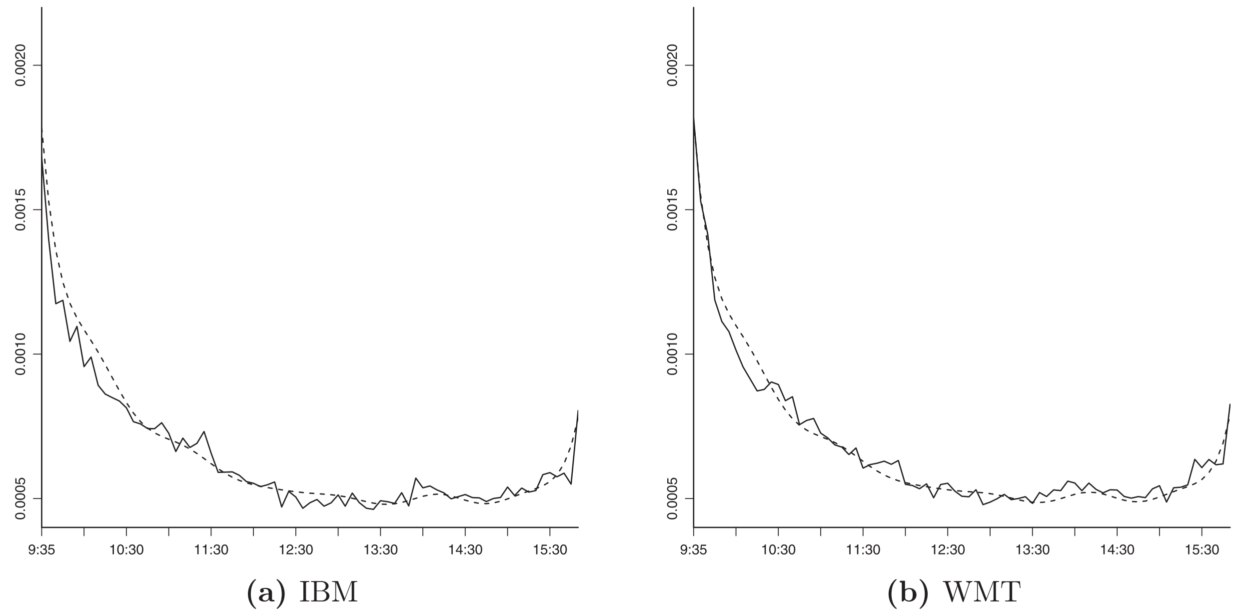


Fig. 3. Average of absolute 5-minute returns and intraday periodic volatility component The plots show the average of intraday absolute 5-minute returns calculated for two stocks, (a) IBM and (b) WMT. In addition, the dashed line denotes the, appropriately scaled, superimposed estimated average intraday periodic volatility component.

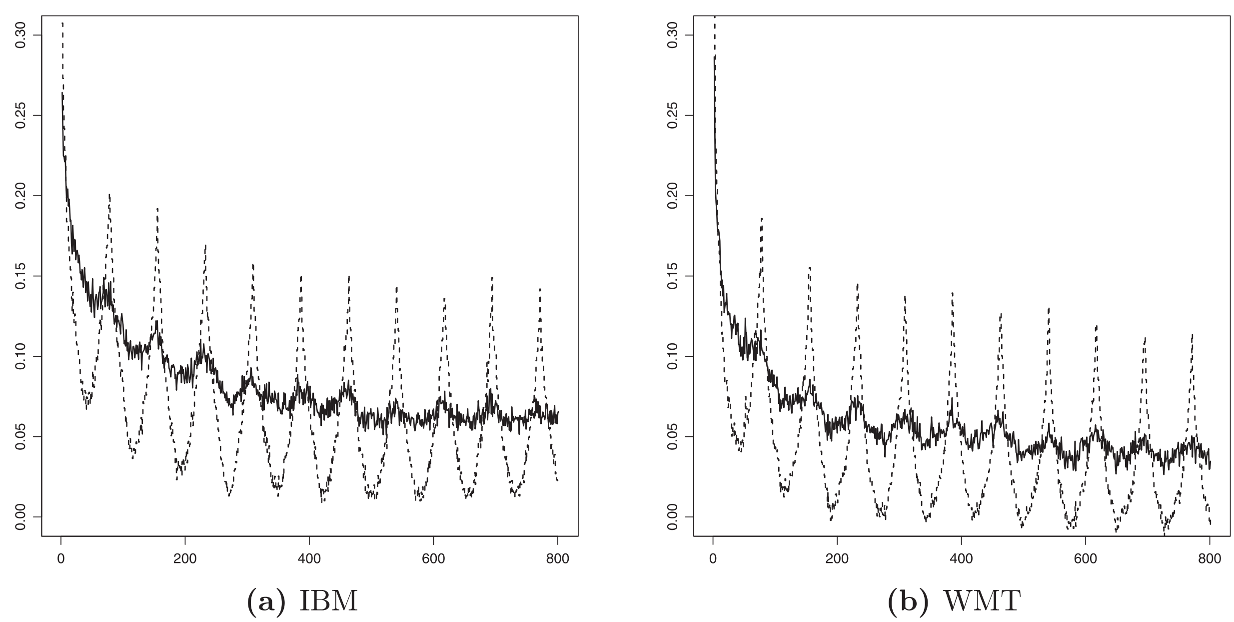


Fig. 4. ACFs of raw and filtered absolute 5-minute returns The plots show ACFs of raw (dashed lines) and filtered (solid lines) intraday absolute 5-minute returns over 800 5-minute lags, which correspond to approximately ten trading days, for two stocks, (a) IBM and (b) WMT.

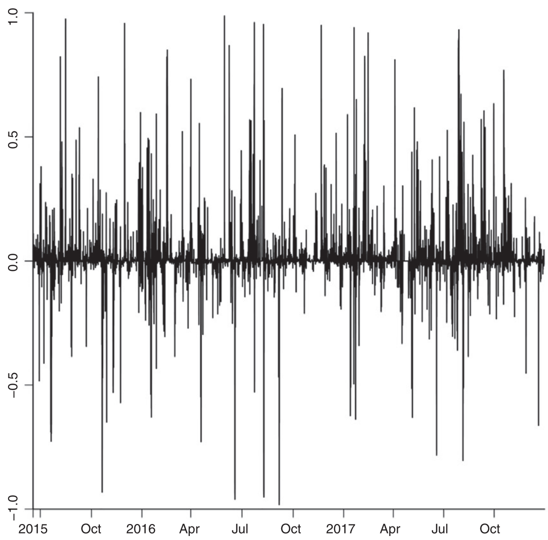
after seven trading days. For WMT, the ACFs of the Twitter count time series behave similarly to its sentiment counterpart with positive and significant lags for up to 10 trading days. Overall, no clear recurring (intraday) pattern can be found in the Twitter time series for our sample of the 30 DJIA constituents.

3.2. Interactions between intraday Twitter sentiment, Twitter count and volatility

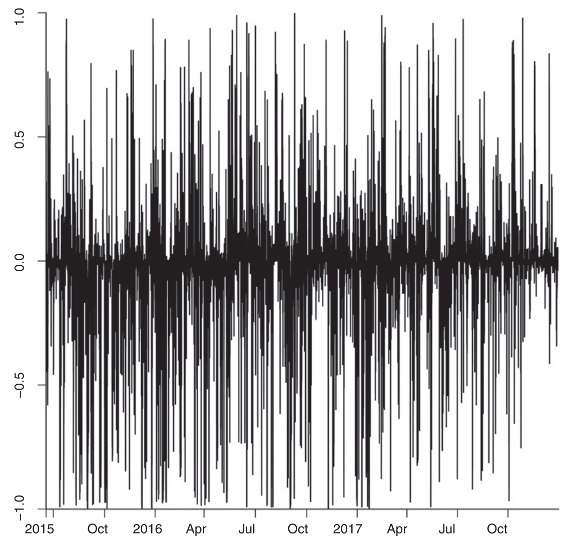
In order to allow for a feedback effect of return volatility, given by the filtered absolute 5-minute returns obtained as discussed in Section 2, to Twitter sentiment as well as Twitter count and vice versa, a simple bivariate VAR model is entertained. Stated in structural form:

$$\begin{bmatrix} 1 & 0 \\ b_{21}^{0} & 1 \end{bmatrix} \begin{bmatrix} R_{t,n}^{*} \\ twit_{t,n} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} b_{11}^{j} & b_{12}^{j} \\ b_{21}^{j} & b_{22}^{j} \end{bmatrix} \begin{bmatrix} R_{t,n-j}^{*} \\ twit_{t,n-j} \end{bmatrix} + \begin{bmatrix} u_{1t,n} \\ u_{2t,n} \end{bmatrix} \quad (3)$$

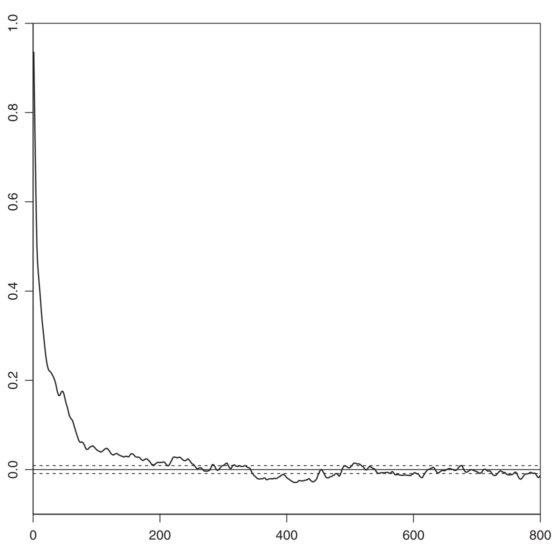
where $twit_{t,\,n}$ denotes either Twitter sentiment or count. For the specification with Twitter count, we need to relax the assumption of Gaussian white noise innovations $\{u_{it,n}\}_{t=1,n=1}^{TN}$ where $i = 1, 2$, $T = 639$, $N = 77$. This assumption is usually made in the VAR context, yet count data are non-negative integers and cannot be normally distributed (Cameron and Trivedi, 1986). The relaxation of the normality assumption of the innovations, however, does not affect our VAR analysis. It has no effect on the estimation of the parameters of the VAR model but is only important for correct in-



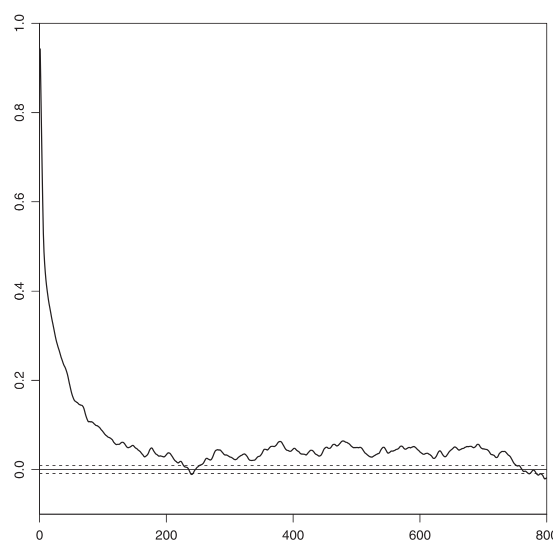
(a) TS: IBM



(b) TS: WMT



(c) ACF TS: IBM



(d) ACF TS: WMT

Fig. 5. Twitter sentiment time series and ACFs Plots (a) and (b) show the time series of Twitter sentiment (TS) for IBM and WMT, respectively. Plots (c) and (d) illustrate ACFs of the TS for these stocks over 800 5-minute lags, which correspond to approximately ten trading days. The dashed lines indicate 95% confidence bounds.

ference, which is not a main issue here. We choose the lag order p of the VAR model according to the average lag length suggested by the Schwarz information criterion (SC) across all 30 DJIA constituents, which leads to $p = 17$ for the specification with filtered absolute 5-minute returns and Twitter sentiment and $p = 18$ for the specification with Twitter count data.[2] Even though the ACFs of the VAR residuals still show some significant spikes for IBM and WMT, in light of the small magnitudes of the coefficient estimates, as reported below, these statistically significant lags do not appear to be of economic relevance.

The results of both VAR specifications are illustrated in Table 1. Since we are mostly interested in the question of whether or not lags of Twitter sentiment and Twitter count have a significant impact on filtered absolute 5-minute returns, only the results for Twitter lags significant at a 10% significance level are displayed. Significant effects might indicate that intraday forecast augmentation of return volatility could be possible using exogenous information from Twitter. Panel A shows these significant autoregressive terms of both Twitter variables throughout both models. The Granger causality tests, which can be found in Panel B of Table 1, support the finding that Twitter sentiment and count indeed hold statistically significant information about future return volatility. The hypothesis that the Twitter variables do not Granger cause volatility can be rejected for both stocks and specifications, except for IBM's Twitter sentiment.[3] However, the actual estimates of lagged Twitter sentiment and count in the VAR specifications are rather small in magnitude, indicating a statistically significant but economically not relevant influence of the Twitter variables on

[2] Robustness checks show that adjusting the lag length for each stock individually does not affect our main estimation results.

[3] An overview over the Granger causality tests for all 30 DJIA constituents can be found in Table A.1 in the appendix.

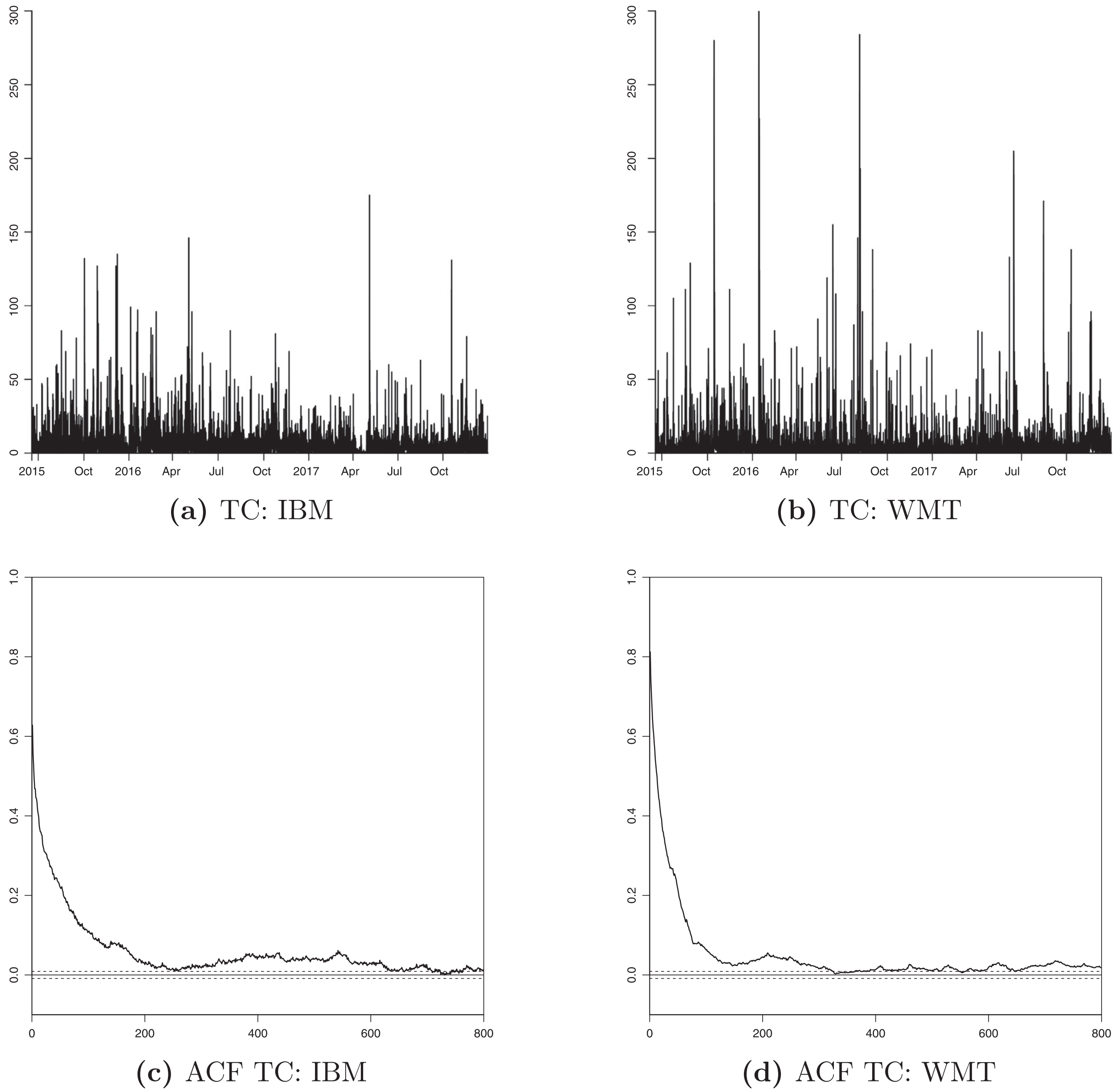


Fig. 6. Twitter count time series and ACFs Plots (a) and (b) show the time series of Twitter count (TC) for IBM and WMT, respectively. Plots (c) and (d) illustrate ACFs of the TS for these stocks over 800 5-minute lags, which correspond to approximately ten trading days. The dashed lines indicate 95% confidence bounds.

the filtered absolute 5-minute return series. This impression is reinforced by the contemporaneous correlation matrices of the reduced form VAR residuals, as presented in Table 2. The correlation between the filtered absolute return and Twitter variable residuals is smaller than 0.02. Furthermore, a decomposition of the filtered absolute returns' forecast error variance shows no relevant contribution of either Twitter variable for all DJIA constituents (less than 2% of the forecast error variance).

Based on the estimation results of the VAR model, we can now investigate the evolution of shocks to either the volatility measure or the respective Twitter variable through the system by means of impulse response analysis. In order to uniquely identify the effect of these shocks, we use a Cholesky decomposition in which return volatility is ordered first, followed by the respective Twitter variable (see Eq. (3)). This ordering implies the exclusion restriction that only shocks to volatility can affect the Twitter variables contemporaneously, whereas shocks to the Twitter variables cannot affect absolute returns in the same period. This restriction appears to be sensible, since one would expect a fundamental shock in volatility to appear first, which then, in turn, influences investor sentiment and activity as captured by the Twitter variables (see, Dimpfl and Jank, 2016; Lux and Marchesi, 1999). Investor sentiment and activity, on the other hand, can be assumed to be contemporaneously affected by stock performance and changes in return volatility. Fig. 7 depicts the impulse responses of volatility and Twitter sentiment to shocks in one of the system variables. A 10% shock in absolute returns leads to a negative reaction in Twitter sentiment for both IBM and WMT. However, this effect is statistically not distinguishable from zero over the first hour (12 lags) after the shock. Only then there appears to be a significant, slightly negative impact of the volatility shock on Twitter sentiment, but only for WMT. A one unit shock in Twitter sentiment leads to minor short-run fluctuations of volatility which are barely distinguishable form zero for both stocks.

For the VAR specification with Twitter count as the second system variable, Fig. 8 shows that a 10% shock in absolute returns

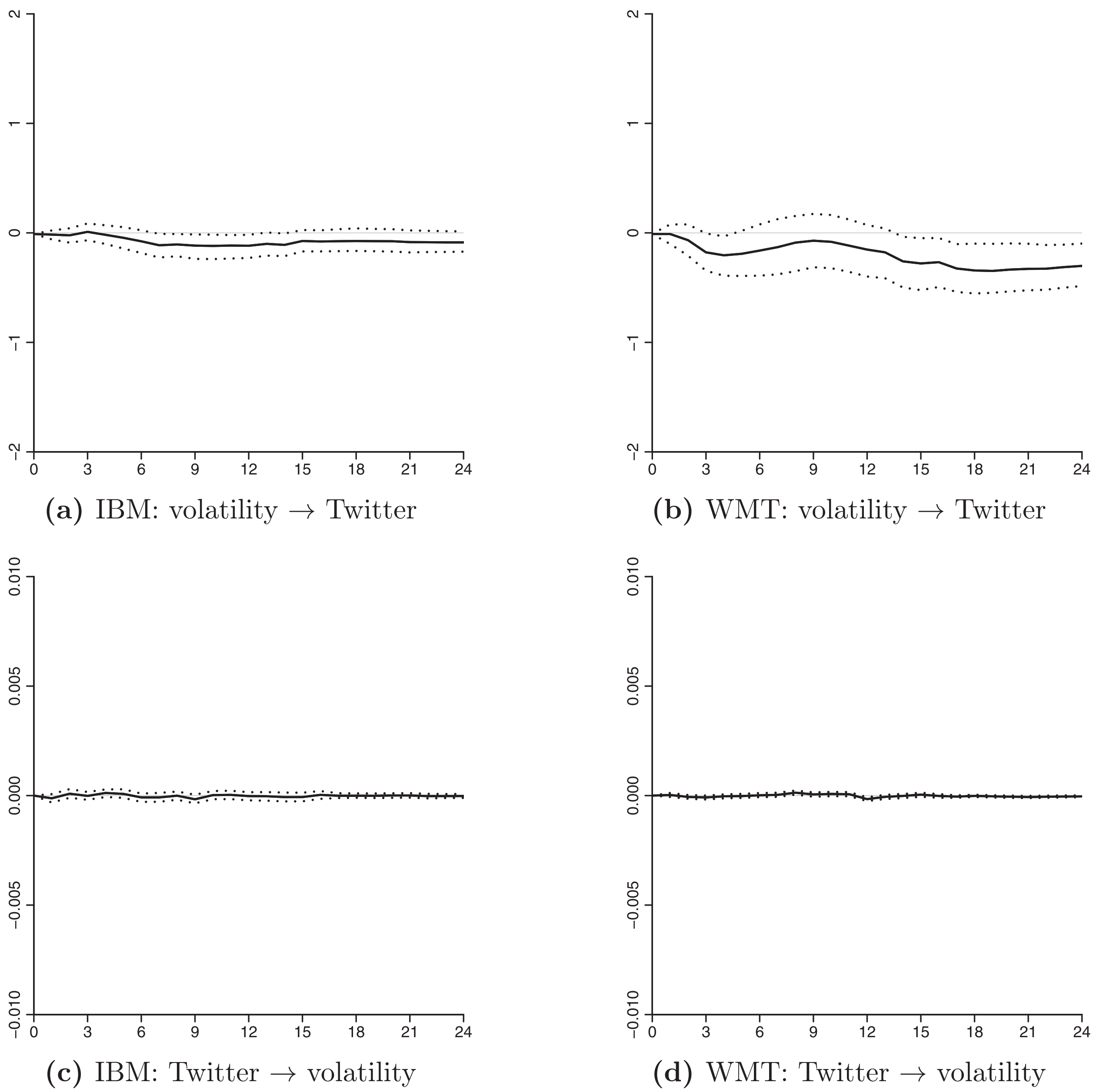


Fig. 7. Impulse response functions Twitter sentiment The plots show orthogonal impulse response functions over 24 5-minute lags for the VAR specification with filtered absolute returns (volatility) and Twitter sentiment as system variables. The dashed lines indicate 95% confidence bounds.

leads to an increase in the number of Tweets. While for IBM this effect is only slightly significant, the WMT stock shows what appears to be a rather persistent, positive reaction from the first period onwards. Turning to the reaction of the filtered returns to a shock in Twitter count, as shown in the two lower graphs, the effect does not appear to be distinguishable from zero.

The results of the impulse response analysis are robust to a reordering of the system variables. All in all, while there are some significant feedback effects between filtered absolute 5-minute returns and the Twitter variables, the prospects for a meaningful forecast augmentation using exogenous information from Twitter seem to be rather poor.

4. Forecasting intraday volatility with twitter information

In light of the previous analysis in Section 3, we choose a different approach to forecast intraday volatility and adapt Corsi's (2009) HAR model to the intraday context. The HAR model is chosen since it is a parsimonious model that has been shown to sufficiently capture the long-memory properties of daily realized volatility (e.g., Andersen et al., 2007; Chiriac and Voev, 2011). The HAR model contains aggregates of the absolute filtered returns and Twitter time series as right hand side variables, which should lead to an improvement in terms of predictive power of the HAR model over the previously estimated VAR model. For example, Dimpfl and Jank (2016) use a HAR model that is augmented

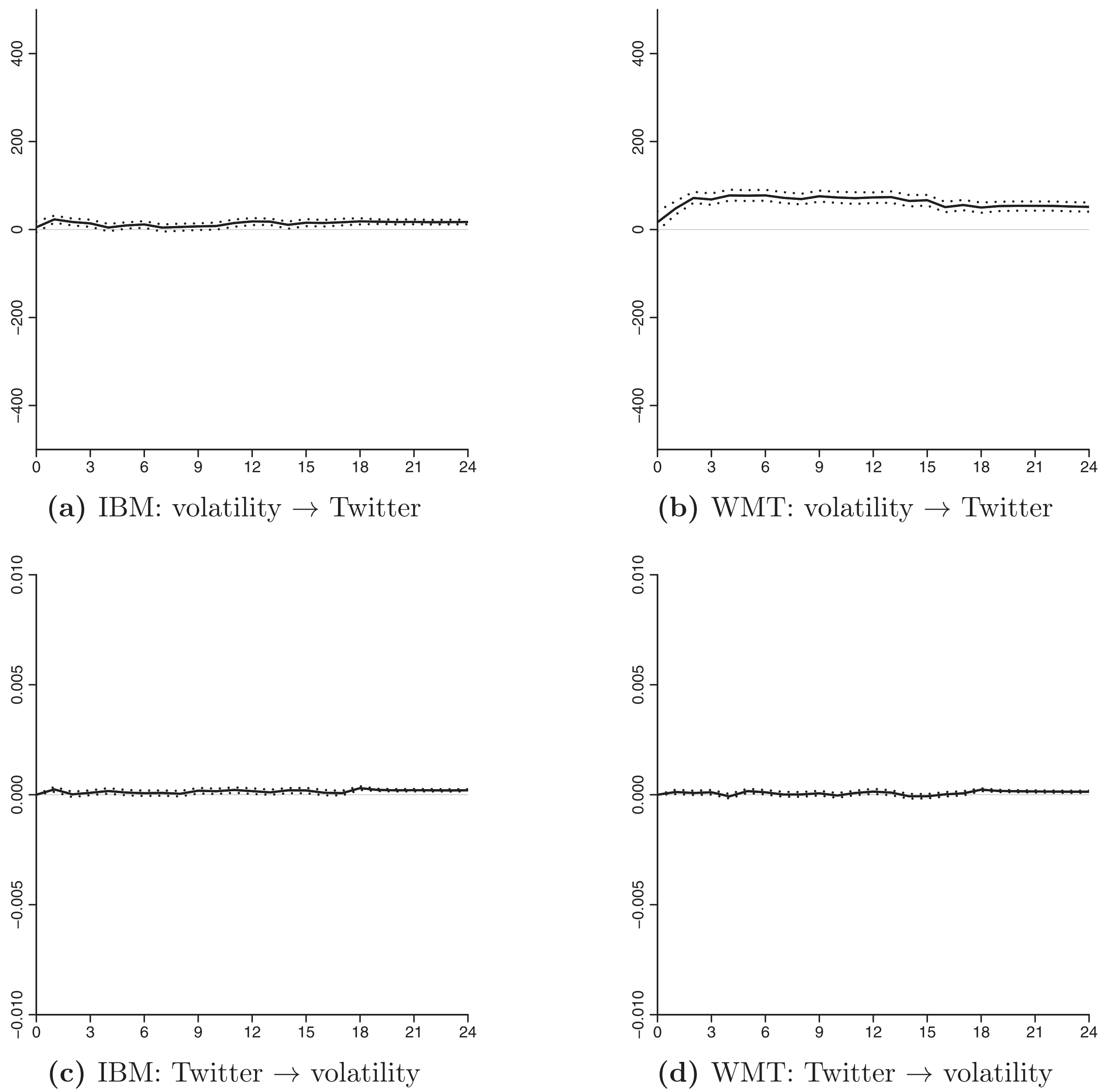


Fig. 8. Impulse response functions Twitter count The plots show orthogonal impulse response functions over 24 5-minute lags for the VAR specification with filtered absolute returns (volatility) and Twitter count as system variables. The dashed lines indicate 95% confidence bounds.

with lagged Google search queries as an additional exogenous variable and find that their model leads to an improvement in forecast precision out-of-sample in comparison to their VAR specification. For our application, however, the model structure of a conventional HAR model applied to our intraday time series would inevitably produce spillover effects and averages of Twitter and volatility variables that are calculated across trading days. As this is not desirable in the intraday context, we facilitate a panel structure in the HAR model using $t = 1, \ldots, 639$ as the cross-sectional unit (trading days) and $n = 1, \ldots, 53$ for intraday periods. Whilst the notation with respect to the indices has not changed in comparison to the VAR model, the HAR model now entails a panel model interpretation. Patton and Sheppard (2015) follow a similar approach in that they set up a panel HAR for volatility modelling based on daily observations to account for firm-specific effects. However, the adaptation of the HAR model to the intraday context has – to the best of our knowledge – not been pursued by other authors so far. The panel HAR model reads as follows:[4]

$$\begin{aligned} R^*_{t,n} &= c + \beta_1 R^*_{t,n-1} + \beta_{12} R^{*12}_{t,n-1} + \beta_{24} R^{*24}_{t,n-1} + \delta_1 twit_{t,n-1} \\ &\quad + \delta_{12} twit^{12}_{t,n-1} + \delta_{24} twit^{24}_{t,n-1} + \gamma_1 sgn(\bar{R}_{t,n-1}) + u_{t,n} \end{aligned} \tag{4}$$

where $sgn(\bar{R}_{t,n-1})$ denotes the sign of the average return in the previous 5-minute interval and $R^{*12}_{t,n-1} = \frac{1}{12}\sum_{j=1}^{12} R^*_{t,n-j}$ and $R^{*24}_{t,n-1} = \frac{1}{24}\sum_{j=1}^{24} R^*_{t,n-j}$ are lagged averages for one and two hours of the filtered returns, respectively. $twit^{12}_{t,n-1}$ and $twit^{24}_{t,n-1}$ are calculated analogously for both Twitter variables. Assuming that (profes-

[4] We have also estimated a HAR model with more lags of the dependent and exogenous variable, as well as different hourly aggregates as independent variables. Since the results stay robust across all models, we have chosen the most parsimonious one.

Table 1
VAR model and Granger causality results The first two columns of Panel A show the results of the VAR model with Twitter sentiment as the second system variable, the last two columns the ones with Twitter count. Only estimates of the respective Twitter variable significant at the 10% level are displayed. Coefficient estimates are multiplied by 10^3. Panel B shows the F-statistics of the Granger causality test. The respective H_0 tested is indicated in the first column. P-values are given in parentheses. Significance of the Granger causality F-statistics at the 10% level is highlighted in bold face.

	Panel A: VAR estimation results $\times 10^3$			
	Twitter sentiment		Twitter count	
	IBM	WMT	IBM	WMT
$twit_{t,n-1}$			0.0024 (0.0001)	0.0012 (0.0192)
$twit_{t,n-2}$	0.2504 (0.0938)			
$twit_{t,n-4}$				-0.0017 (0.0043)
$twit_{t,n-5}$				0.0019 (0.0013)
$twit_{t,n-9}$			0.0011 (0.0802)	
$twit_{t,n-10}$	0.2807 (0.0696)			
$twit_{t,n-12}$		-0.2104 (0.0041)		
$twit_{t,n-13}$		0.1922 (0.0088)		
$twit_{t,n-14}$				-0.0017 (0.0039)
$twit_{t,n-18}$			0.0019 (0.0021)	0.0018 (0.0006)

	Panel B: Granger causality test			
	Twitter sentiment		Twitter count	
H_0	IBM	WMT	IBM	WMT
$R^* \nrightarrow twit$	1.2607 (0.2076)	0.8019 (0.6929)	**5.9968** (0.0000)	**40.4163** (0.0000)
$twit \nrightarrow R^*$	1.0957 (0.3503)	**1.7018** (0.0352)	**3.2663** (0.0000)	**2.8456** (0.0000)

sional) investors with access to intraday Twitter data can react swiftly to changes in individual-level stock return volatility and the Twitter variables, further lags are omitted. The sign variable is added to the model to account for the asymmetric effect of returns, i.e. negative returns have a larger effect on volatility than positive returns. The panel HAR of Eq. (4) is subsequently estimated using fixed effects estimation with fixed effects for trading days and adjusted standard errors to account for heteroscedasticity as well as serial correlation.[5]

For forecasting purposes, the overall sample is split into a sample containing 90% (44,283 observations) of the data to which the panel HAR model is fitted. The remaining 10% (4,920 observations) of the data are used to assess the forecasting performance of the model out-of-sample. This is achieved by predicting the absolute 5-minute returns using the coefficient estimates of Eq. (4) together with the exogenously given Twitter sentiment and count data and comparing the predicted values to the actual filtered absolute 5-minute returns. As a measure for forecast performance the root mean squared error (RMSE) is used.

Table 3 summarizes the panel HAR model with Twitter sentiment (Panel A) and Twitter count (Panel B) as additional exogenous variables. For both stocks, lagged values of the respective Twitter variable occasionally show significant coefficient estimates.

[5] The Hausman (1978) test rejects a random effects model in favor of a model with fixed effects. Arellano (1987) standard errors are used, however, the results are robust to other types of robust standard errors.

Table 2
Contemporaneous residual correlation matrices The table shows the contemporaneous correlations between the reduced form VAR residuals. For the VAR in Panel A Twitter sentiment is used as the second system variable, in Panel B Twitter count.

Panel A: Twitter sentiment

$$\text{IBM:}\quad \begin{array}{c|cc} & R^* & twit \\ \hline R^* & 1 & -0.0079 \\ twit & -0.0079 & 1 \end{array} \qquad \text{WMT:}\quad \begin{array}{c|cc} & R^* & twit \\ \hline R^* & 1 & -0.0032 \\ twit & -0.0032 & 1 \end{array}$$

Panel B: Twitter count

$$\text{IBM:}\quad \begin{array}{c|cc} & R^* & twit \\ \hline R^* & 1 & 0.0068 \\ twit & 0.0068 & 1 \end{array} \qquad \text{WMT:}\quad \begin{array}{c|cc} & R^* & twit \\ \hline R^* & 1 & 0.0191 \\ twit & 0.0191 & 1 \end{array}$$

Table 3
Panel HAR in-sample results The table presents the in-sample parameter estimates of the panel HAR model. Panel A shows the results for IBM and WMT with Twitter sentiment as exogenous variable, Panel B with Twitter count as exogenous variable. P-values are given in parentheses.

	Panel A: Twitter sentiment		Panel B: Twitter count	
	IBM	WMT	IBM	WMT
$R^*_{t,n-1}$	0.0441^{**} (0.0227)	0.0540^{***} (0.0000)	0.0440^{**} (0.0226)	0.0536^{***} (0.0000)
$R^{*12}_{t,n-1}$	0.1496^{***} (0.0027)	0.0971^{**} (0.0282)	0.1496^{***} (0.0029)	0.1013^{**} (0.0203)
$R^{*24}_{t,n-1}$	-0.0805^{**} (0.0348)	-0.1228^{***} (0.0000)	-0.0805^{**} (0.0371)	-0.1230^{***} (0.0000)
$sgn(\bar{R}_{t,n-1})$	0.0000 (0.8952)	0.0000 (0.3343)	0.0000 (0.8674)	0.0000 (0.3169)
$twit_{t,n-1}$	0.0000 (0.7516)	0.0000 (0.7270)	0.0000^{***} (0.0065)	0.0000^{*} (0.0714)
$twit^{12}_{t,n-1}$	-0.0001 (0.5852)	0.0001^{**} (0.0487)	0.0000 (0.4354)	0.0000 (0.3725)
$twit^{24}_{t,n-1}$	0.0001^{**} (0.0288)	0.0000 (0.9384)	0.0000 (0.9543)	0.0000 (0.1507)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Panel HAR forecast evaluation Overview of the RMSE ($\times 10^4$) for the out-of-sample forecast of the panel HAR model with three specifications: first row HAR model without exogenous variable; second row with Twitter sentiment (*TS*) as exogenous variable; last row with Twitter count (*TC*) as exogenous variable.

	IBM	WMT
HAR	6.8934	9.0461
HAR + *TS*	6.8798	9.0309
HAR + *TC*	6.8706	8.8692

However, their magnitudes are very small, which does not allow any further meaningful interpretation of the coefficients.[6]

Considering these results, the RMSEs – our forecast accuracy measure – as shown in Table 4 should not surprise: Twitter can

[6] These results are robust to different lag structures as well as to a panel HAR model which includes both Twitter sentiment and count as exogenous variables.

only slightly lower the forecasting errors across the different HAR specifications and thus does not appear to hold any additional information that is of practical relevance for forecasting volatility.

To sum up, the results of the panel HAR models, as shown above, are in line with the results of the VAR models of the previous section: in terms of statistical significance Twitter sentiment and count are indeed relevant for return volatility. Nevertheless, the influence of exogenous Twitter information on the stocks' volatility is, economically speaking, small. With respect to forecasting, Twitter's predictive power can be described as weak at best, just as suggested by the preceding empirical analysis.[7] Including Twitter sentiment and Twitter count does not appear to improve forecast performance significantly.

While we have presented detailed results for two stocks only, Table A.1 in the appendix sums up the results of our analyses for all constituents of the DJIA. One noticeable difference in our results among the DJIA constituents is a link that exists with the stocks' average trading volume. DJIA constituents that rank low in trading volume more often show a statistically significant influence of Twitter sentiment and count than those with a high average trading volume. While this influence does not appear to be of economic significance for any of the 30 stocks, our results of both the HAR and VAR model are thus not entirely robust across all 30 constituents of the Dow Jones. Only for the most liquid stocks of the Dow Jones can we rule out a statistically significant effect of Twitter on the respective stock's volatility.

5. Concluding remarks

In this paper we use intraday Twitter sentiment and Twitter count data to measure investors' interest in individual-level stocks, in our case the constituents of the DJIA. Measuring intraday volatility with absolute 5-minute returns and after accounting for the pronounced intraday periodicity in absolute returns, we find that there are indeed statistically significant feedback effects of return volatility to Twitter sentiment as well as Twitter count and vice versa in a bivariate VAR framework. However, estimated coefficients are of small absolute magnitude and the effects do not have a significant economic impact. While Twitter sentiment and count Granger-cause return volatility, the contemporaneous correlation between volatility and both Twitter variables as well as the results from forecast error variance decompositions indicate that incorporating exogenous information from Twitter into intraday prediction models for return volatility is unlikely to have a significant impact on forecast performance. We adapt the HAR model of Corsi (2009) to the intraday context and estimate a panel HAR model, augmented with lagged Twitter sentiment and Twitter count information. As suspected from the preceding analysis, there are no gains in out-of-sample forecast performance, compared to models without exogenous Twitter information. We present our results for stocks of two companies (IBM and WMT) but results are similar for all constituents of the DJIA and different model specifications.

Thus, it seems that intraday information from Twitter about individual-level stocks, as provided by commercial data vendors, does not constitute a valuable source of information for future volatility and professional, highly active investors with access to such data do not benefit with regards to intraday volatility assessment and forecasting. Our results are in line with the notion of professional investors: the performance of liquid blue-chip stocks such as the DJIA constituents should be linked to information related to fundamentals, indicating that investor sentiment obtained from Twitter should only have a negligible effect on financial volatility. This is even more so, since the intraday frequencies considered here are too high for investors, other than professional investors, to react appropriately to such information. Thus, the empirical analysis of the effects of investor sentiment obtained from social media platforms such as Twitter on stock return properties are most likely rendered more interesting for lower frequencies. This is consistent with previous literature that mainly uses daily observations (e.g., Bollen et al., 2011; Sprenger et al., 2014b). While we rank our overall results by average trading volume, we only consider constituents of the DJIA in this paper. Future research should further investigate the feedback effects between investor sentiment obtained from social media platforms and intraday volatility of less liquid stocks, in order to test the validity and robustness of the findings presented in this paper.

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Appendix A

A1. Fourier flexible form estimation procedure

The logarithm of the squared periodic component in Eq. (1), $ln(s_{t,n}^2)$, can be estimated from the following FFF regression:

$$2ln\left(\frac{|R_{t,n}-\bar{R}|}{\hat{\sigma}_t/N^{1/2}}\right) = c + \delta_{0,1}\frac{n}{N_1} + \delta_{0,2}\frac{n^2}{N_2} + \sum_{p=1}^{P}\left(\delta_{c,p}cos\frac{2\pi p}{N}n + \delta_{s,p}sin\frac{2\pi p}{N}n\right) + \upsilon_{t,n} \tag{A.1}$$

where $\bar{R}$ denotes the sample mean of the 5-minute returns (might also be set equal to zero, since it is not statistically different from zero for any stock in the sample), $\hat{\sigma}_t$ is a previously obtained estimate of the daily volatility factor, N refers to the number of return intervals per trading day (here $N = 77$), P is a tuning parameter for the number of trigonometric terms, and $N_1 = (N+1)/2$ as well as $N_2 = (N+1)(N+2)/6$ are normalizing constants. In accordance with Bollerslev et al. (2000) and other research, the number of polynomial terms is restricted to two.

We use an A-PARCH specification to estimate σ_t in a first step. In addition, a simple AR(1)-GARCH(1,1) specification serves as a benchmark. Results are not much different compared to the A-PARCH specification. In fact, for many stocks the estimates of σ_t are very similar across these two models. Our model specifies the mean equation in terms of an AR(1) process, since for more than half of the stocks in the sample such an autoregressive structure seems appropriate when considering the statistical significance of the lagged return coefficient. Specifications have also been tested with an MA(1) structure in the mean equation. However, the coefficient of the MA term is statistically significant for a smaller number of stocks. We choose the same model for all stocks, instead of estimating different models for each of the DJIA constituents. More sophisticated ARMA structures are not applied to the mean

[7] In addition to the panel HAR model, an ARMA model with exogenous variables and up to 19 lags has been estimated too. Though this model is over-parameterized, a necessity to get rid of the autocorrelation in the residuals, the results support the weak predictive power of both Twitter variables that the panel HAR model has found. Results of the ARMA model are available upon request.

equation, since the simple autoregressive structure already delivers good empirical results. For the A-PARCH(1,1), the mean equation is given by:

$$R_t = \mu_0 + \mu_1 R_{t-1} + \varepsilon_t \tag{A.2}$$

The variance equation is modeled in the following way:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^{\delta} + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta} \tag{A.3}$$

where $\delta \in \mathbb{R}^+$ is a Box-Cox transformation of σ_t, and γ the coefficient of the leverage term. Estimates are obtained by assuming conditionally skewed-t distributed standardized innovations, $\varepsilon_t\sigma_t^{-1}$, and the 5-minute volatility estimator is calculated as $\hat{\sigma}_{t,n} = \hat{\sigma}_t/N^{1/2}$.

In the second step, the parameters of the FFF specification are estimated by OLS. The log-transformation is used to draw in outliers and to render the regression more robust. In line with the literature, $P = 6$ is assumed to capture the basic shape of the intraday volatility pattern. Experimenting with different values for P we find that for $P < 6$ the trigonometric terms of different orders were statistically significant for most stocks. However, for $P > 6$ higher order trigonometric terms are only statistically significant for a handful of stocks. Thus, $P = 6$ is chosen as an appropriate order of expansion. Denote the raw absolute 5-minute returns by $|R_{t,n}|$, the filtered 5-minute absolute returns are then given by:

$$R_{t,n}^{*} = \frac{|R_{t,n}|}{\hat{s}_{t,n}} \tag{A.4}$$

where $\hat{s}_{t,n}$ denotes the normalized estimate for the periodic component, as obtained from the FFF regression, and let $\hat{x}_{t,n}$ denote the estimated value of the right-hand side of the FFF specification. The standardized periodic component is then given by:

$$\hat{s}_{t,n} = TN\frac{exp(\hat{x}_{t,n}/2)}{\sum_{t=1}^{T}\sum_{n=1}^{N} exp(\hat{x}_{t,n}/2)} \tag{A.5}$$

where now $\frac{1}{TN}\sum_{t=1}^{T}\sum_{n=1}^{N}\hat{s}_{t,n} \equiv 1$.

Apart from daily A-PARCH or GARCH models, Engle and Gallo (2006) propose to model the daily volatility component based on the square root of daily realized variance, which is given by $RV_{t,N} = \sum_{j=1}^{1/N} R_{t-1+jN,N}^2$. Similar to the calculation above, the 5-minute volatility estimator is simply given by $\hat{\sigma}_{t,n} = (RV_{t,N}/N)^{1/2}$. In order to reduce the impact of microstructure effects, 10-minute and 15-minute returns are used in the realized variance calculation. Results are robust to calculating the daily volatility component using the square root of daily realized variance over both 10-minute and 15-minute intraday returns.

A2. Overview: Results for all DJIA constituents

In Table A.1 we present an overview of the statistical significance of Twitter sentiment and count in both VAR and HAR models as well as the Granger causality results for both VAR specifications, considering the whole sample of all 30 DJIA constituents. Additional data on trading volume is taken from Thomson–Reuters Datastream for the period from June 18, 2015 to December 29, 2017.

Table A1
Model results for all DJIA constituents The table summarizes our results for all DJIA constituents in descending order of average trading volume (column 2). Each stock with at least two significant Twitter variables is marked with × in columns 3 to 5. Column 3 summarizes results for both VAR models. Columns 4 refers to the panel HAR model in Eq. (4) and column 5 to an alternative model with additional autoregressive terms for 30 minutes and three hours for both R^* and *twit*. F-statistics of the Granger causality test can be found in columns 6 to 7 and columns 8 to 9 for Twitter sentiment and count, respectively. The H_0 tested is indicated above each column. Significance on the 10% level is highlighted.

					Sentiment		Count	
Ticker	Volume	VAR	HAR1	HAR2	$R^* \not\to T$	$T \not\to R^*$	$R^* \not\to T$	$T \not\to R^*$
GE	453.81	×			**2.1684**	0.6976	**5.9543**	**2.8337**
AAPL	367.75			×	**1.4721**	0.6154	**5.6040**	**6.0759**
MSFT	285.29				0.9605	**1.4860**	1.2739	0.8573
PFE	264.22	×			1.0670	0.1066	**3.8680**	1.1818
INTC	247.81				1.3820	0.3625	**2.9899**	**1.7498**
CSCO	233.83			×	1.0993	**1.5003**	0.7855	**2.8876**
JPM	154.75				**1.9473**	0.9993	**1.8870**	1.0505
VZ	148.85				0.7375	0.6828	0.4858	1.1721
KO	128.42				1.2546	1.3345	0.9386	**1.7326**
XOM	123.74	×	×		1.2731	0.7470	1.1769	**1.7594**
MRK	102.41				0.6854	1.1696	1.2390	0.4046
PG	96.07				0.6206	0.9298	**33.2960**	**1.5941**
NKE	94.80	×			0.5325	1.2436	**3.4281**	**2.7298**
WMT	94.38	×	×		0.8019	**1.7018**	**40.4163**	**2.8456**
V	85.88		×	×	0.8170	0.5741	1.3083	1.0021
DIS	82.61	×			**1.7140**	0.6003	**25.7273**	**9.8504**
DD	76.55	×			1.2967	1.0419	**9.6421**	**4.7287**
CVX	76.36	×			1.1816	1.1762	**3.0121**	**2.4587**
JNJ	69.96	×			**2.6715**	**2.1258**	**3.4540**	**2.6726**
CAT	52.74				**2.9053**	1.0739	**10.3373**	**4.5908**
HD	48.94	×			0.9799	**2.1205**	**9.3463**	**3.3585**
AXP	48.54	×			0.7538	**2.5288**	**15.9147**	**6.1008**
MCD	48.41	×		×	1.0901	1.0417	**1.9112**	**1.5883**
IBM	42.22	×	×		1.2607	1.0957	**5.9968**	**3.2663**
UTX	40.30	×			0.6168	**1.8660**	**20.1767**	**18.2685**
BA	37.95	×			0.8354	0.6984	**8.1744**	**2.1790**
UNH	35.05	×			0.8481	1.3064	**4.9244**	**2.4981**
GS	33.80	×			1.0125	**1.6159**	**3.5307**	**2.1091**
MMM	20.98				**1.5369**	0.9916	0.9079	**1.6085**
TRV	16.64				0.5003	1.1115	0.8267	0.5104

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