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Silence is not Golden Anymore?

Social media activity and stock market valuation in Europe

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ABSTRACT

We investigate the link between social media activity and market valuation of listed European companies over the period January 2018 – June 2020. Using a large novel dataset from 39 European capital markets, we first provide a comprehensive "big picture" of social media activity of European listed companies, using data from all European capital markets. Second, we show that greater Twitter activity is associated with increased shareholders' returns. Third, we find that portfolios with a larger number of tweets posted by a company exhibit larger market risks. Our findings support the idea that investors should consider social media activity when implementing investment strategies.

Keywords – stock markets, valuation, CAPM, Twitter, social media, investor attention, information asymmetry, disclosure.

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1. Introduction

According to the strong form of the efficient market hypothesis (EMH), market prices fully reflect all available information (Fama, 1970). However, Kahneman (1973) points out that the amount of information available is much greater than people can absorb, and that attention is a scarce resource. Recent empirical studies have suggested that the attention investors pay to the market significantly influences asset pricing (e.g., Andrei & Hasler, 2015; Da, Engelberg & Gao, 2011). Concurrently, previous studies demonstrate that greater information asymmetry between investors increases transaction costs and lowers liquidity for trading shares, resulting in higher required rates of return. The degree of information asymmetry may not always be a firm's choice. According to Aslan et al. (2011), smaller and younger firms, with more insider holdings, with greater institutional holdings, and smaller analyst coverage, and also those operating in industries like oil and petroleum products, construction, textiles, and retail, are all more likely to have more severe informational asymmetry.

Firms are able to control their information environment and achieve a reduction in the cost of equity using social media (Guindy, 2021). Most existing studies on social media refer to the efficient market hypothesis or the investor attention hypothesis. On the one hand, if a reduction in information asymmetry is at play, it should lower the required rates of return. On the other hand, according to the "price pressure hypothesis" or the "attention theory", individual investors buy stocks that attract their attention due to a lack of resources and time (Barber & Odean, 2008). Recent empirical analyses on behavioral finance suggest that public attention can influence stock prices, even without any new information.

In this article, we investigate the link between social media activity and market valuation of listed European companies. Indeed, despite the immense development of IT tools and technologies, no attempt to compare the impact of social media on stock prices in the European markets has been made since the birth of interest in the impact of social media on financial markets (Antweiler & Frank, 2004). This may be explained by the fact that the authorities regulating and supervising North American capital markets allow companies to choose their channels of communication with investors (including social media), while it is not permitted in Europe[2]. Indeed, in April 2013 SEC issued a report that made clear that companies can use social media outlets like Facebook and Twitter to announce key information in compliance with Regulation Fair Disclosure (Regulation FD) so long as investors have been alerted about which social media will be used to disseminate such information. By the third quarter of 2014, 84 percent of sampled U.S. firms had a corporate Twitter account and, in a global sample, 70 percent of firms with corporate accounts had a history of tweeting investor relations content (Investis, 2015). In the European Union there are strict rules and procedures to follow when a listed company has important updates to share with the market. The rules on the dissemination of inside information in the European Union are to ensure that all investors have simultaneous access to accurate information in national databases, the so-called Officially Appointed Mechanisms ("OAMs") and know where they can find it (Electronic System of Information Filing system followed by information on the company's website). The companies may post its news on social media, but only after it has first made it available via a regulatory information service. Due to these regulatory differences, conclusions drawn from US datasets may not necessarily hold for other capital markets. Therefore the aim of this article is to provide a more comprehensive analysis of all European markets.

Literature on social media can broadly be divided into two approaches according to measures of investor attention: indirect or direct. The following measures are applied regarding indirect proxies for investor attention: extreme returns, trading volume news, headlines, and advertising expense. Following the direct approach, proxies refer to Google's Search Volume Index (SVI) or the number

[2] Bank et al. (2019) is one of the few studies that carried out such investigation but only for one stock market (Borsa Istanbul).

of tweets produced by a company, the number of tweeting days and the number of words contained in tweets, the number of retweets, and the number of followers. The other classification concerns the process of creating information on social media. According to Blankespoor et al. (2014) and Rakowski (2018), there are two separate but corresponding mechanisms: disclosure (supply of information) and dissemination (consumption of information). Disclosure can be measured by the number of tweets produced by a company, the number of tweeting days, and the number of words in the tweets. Dissemination can be proxied by the number of retweets, the number of followers of a company's Twitter account and the Google's Search Volume Index (SVI). Guindy (2021) argues that literature on social media may be classified by the type of Twitter participant: investors, corporate executives, direct company communication. Due to differences in regulatory environments concerning disseminating channels in US and Europe we addresses that last category. This issue may be particularly important for firms which do not receive broad news dissemination via traditional intermediaries, such as the press.

Using a large novel dataset, we first provide a novel and comprehensive "big picture" of social media activity of European listed companies. We find differences in trading behavior among companies using Twitter. Our results confirm the findings of previous studies demonstrating that the use of Twitter to communicate information is associated with higher shareholder returns, consistent with Cole et al. (2015). Thus, the "investor attention hypothesis" based on Barber and Odean (2008) is validated.

We contribute to the existing literature by showing that investors who are investing in companies that actively use social media can earn higher rates of return, compared to investors whose portfolios consist of companies not using social media. However, it is important to note that company tweets increase information dissemination (Alexander & Gentry, 2014; Blankespoor et al., 2014). In addition, according to Rantanen et al. (2019), sudden reactions and comments online can strengthen or degrade a business's reputation faster than ever before.

The rest of the study proceeds as follows. Section 2 details a literature review and hypotheses development. Section 3 outlines the research method, data, and descriptive statistics. Section 4 analyzes the empirical results. The final section offers conclusions and discussions.

2. Literature review and hypotheses development

Traditional models of asset valuation assume that information is instantly reflected in prices of financial instruments. This assumption means that investors pay equal attention to all assets, and at the same time have equal access to information. However, in practice, one party to a financial transaction often has limited information on the transaction (Bali et al., 2021). The occurrence of information asymmetry on financial markets entails many crucial problems, such as adverse selection, moral hazard, free-riding and herding behavior. Therefore, shares of companies that have a weaker presence in media (in general) should offer higher profits to compensate investors for costs resulting from imperfect allocation caused by incomplete information.

Concurrently, behavioral finance relaxes the assumption of traditional models of financial markets by incorporating observable, systematic and human departures from rationality (Barber & Odean, 2008). As claimed by Shleifer and Summers (1990), investors are not rational, and changes in investor moods affect stock prices. It must also be remembered that when buying stocks, investors choose from hundreds if not thousands of financial instruments. There are cognitive and time limitations on the amount of information they can process. Generally, human beings are not able to rank hundreds or even thousands of alternatives, especially if they need to be assessed in many dimensions. According to Odean (1999) investors cope with the problem of choosing from thousands of various financial instruments by limiting their searches to stocks that have recently caught their attention.

In reality, attention is a rare (Kahneman, 1973) and limited quality. Moreover, there is abundant literature suggesting that investors do have limited attention and overlook a lot of publicly available information (Hirshleifer et al., 2009). Relying on limited attention as one of the psychological biases resulting from information processing (Tan & Tas, 2019) and the mechanism of slow diffusion of information, Barber and Odean (2008) in their "attention theory", suggest that attention causes buying pressure in uninformed retail investors. Uninformed individual retail investors do not have enough time or resources to analyze thousands of stocks, so they are usually considered uninformed, boisterous, and interested in speculative transactions. Most recent research on behavioral finance shows that a mere interest in the public sphere is enough to influence stock prices, even if new information does not surface. This is why investors who want to optimize their portfolio must understand how investor attention in the public sphere affects stock prices (Lee et al., 2021).

Testing of the investor attention hypothesis is still difficult as there are no direct measures of attention. There are indirect measures that traditionally include: turnover (Barber & Odean, 2008; Gervais, Kaniel, & Mingelgrin, 2001; Hou, Peng & Xiong, 2008), coverage in news and press headlines (Barber & Odean, 2008; Yuan, 2015), advertising outlays (Chemmanur & Yan, 2009; Grullon, Kanatas, & Weston, 2004; Lou, 2014), price limits (Seasholes & Wu, 2007) and search frequency in Google (Da, Engelberg & Gao, 2011).

While the impact of traditional professional sources of investor information have been thoroughly studied (Barber & Odean, 2008; Fang & Peress, 2009; Ben-Rephael, et al., 2017), social media impact, despite being a subject of empirical analysis, is in question. Empirical evidence on the social media activity of companies, commentators, or followers, etc., is not consistent (Blankespoor et al., 2014; Prokofieva, 2015; Guindy & Riordan, 2017; Mazboudi & Khalil, 2017). The same applies to analyses of social media impact on the market value of listed companies (Wu et al., 2022; Rakowski & Shirley, 2020; Ranco et al., 2015). Bank et al. (2019) is one of the few studies that was carried out for one of the European stock markets (Borsa Istanbul). Their investigation did not confirm that greater Twitter activity of listed companies result in a statistically significant increase of abnormal rates of return. CAPM regression results for the portfolios generated according to the number of followers, the number of tweets and Twitter membership, had statistically insignificant and negative alphas. This result corresponded with market betas higher than 1 in portfolios with high values in the metrics of the number of followers, the number of tweets and Twitter membership. Portfolio returns with superior Twitter performance were more sensitive to changes in market returns.

Interactions on social media may be the main source of information for individual investors and it may increase the quality of information exchange and thus the attractiveness of the capital market. By reaching a wide range of investors, social media may relax certain market imperfections on the information level even if it does not supply true or new information. Tweets, as such, are largely not the primary source of information, but they do affect its dissemination (Alexander & Gentry, 2014; Blankespoor et al., 2014). Furthermore, numerous studies show that companies using Twitter actively build long-term relationships with their stakeholders and reinforce a positive opinion about the company (Abitbol & Lee, 2017; Millham & Atkin, 2016; Saxton & Waters, 2014). Chae & Park (2018) point out that communication through Twitter has a different scale than communication through traditional media. This is down to the type of user and interactions that this platform enables. This means that communication is less formal but has higher visibility and emotional impact on users. What is more, Araujo and Kollat (2018) claim that effective CSR communication on Twitter can influence an organization’s public assessment, thus increasing stakeholders’ identification with the company and consequently, generating a better reputation for a company as a long-term effect.

This is why company use of Twitter may reduce information asymmetry and thus boost the effectiveness of the entire market. In such a case, neither a technical nor a fundamental analysis will allow investors to obtain greater profits than those they are able to obtain if they have a portfolio of randomly selected stocks (with at least comparable risk) (Malkiel, 2003). Previous research has demonstrated that information asymmetry translates into higher required rates of return (Guindy, 2021). The information asymmetry perspective suggests that ceteris paribus, companies wishing to maximize their value try to reduce the degree of information asymmetry by introducing techniques which help them to disseminate news. To test the implication of the information asymmetry perspective, the following hypothesis is formulated:

H1: By reducing information asymmetry, companies that are active on Twitter have lower rates of return than stocks of companies not as active on social media.

In contrast, when referring to the "attention theory", attention creates buying pressure in uninformed retail investors. Individual investors are buyers of attention-grabbing financial instruments, e.g., stocks that are the subject of news, stocks with a high abnormal trading volume and stocks with extreme one-day returns. Attention-driven buying results from the difficulty that investors have in analyzing thousands of stocks they can potentially buy. Thus, we hypothesize that many investors consider purchasing only those stocks that have caught their attention. Social media, Twitter in particular, is what generates attention nowadays.

H2: Since attention is limited, stocks of companies that are active on Twitter have higher rates of return that stocks of actors not as active on social media.

3. Research method, data, and descriptive statistics

This section describes the data sources used in this paper, outlines the methodology to construct the main variables of interest, and provides summary statistics of the key variables.

Our main aim is to answer the question whether activity on social media affects the stock prices of companies listed on European markets (see Table 1 for existing empirical evidence, mostly focused on North American stock markets). There are numerous platforms available for corporate use, with Twitter, Facebook, YouTube, and LinkedIn being some of the most popular. However according to Best and Carol (2019) shareholders are less likely to seek out press releases than they are to subscribe to a company's Twitter feed. Recent research (Nuseir & Qasim, 2021) has showed that Twitter is a predominantly important social media outlet for financial disclosure and additional dissemination of corporate information. Due to the fact that we concentrate on information communicated by a firm we chose as a proxy the number of tweets by a firm as they can be thought of as feature constituting disclosure. Due to length of our research period (January 2018 to June 2020), number of local markets (39) and the number of the companies included in our dataset (initially more than 65 thousand) we skip other proxies of European listed companies' social media activity.

In this study, as in papers by Fang & Peress, (2009) and Bank et al. (2019), the sorted portfolios approach was adopted, which is standard while testing asset pricing models, analysing price anomalies, or identifying profitable investment strategies (Cattaneo et al, 2020). The daily number of tweets was used as a criterion for sorting the portfolios. For this metric, the related firms are sorted from the highest number of produced tweets (1^{st} portfolio) per day to the lowest (4^{th} portfolio), the stocks of each firm are divided into four equal portfolios, and each portfolio is assumed to be held for the relevant period.

Table 1: Metrics describing Twitter activity and research samples description

Researcher	Metrics	Country	Number of observations	Research period	Number of companies
Bank et al. (2019)	– number of followers – increase in number of followers, – number of tweets – Twitter membership	BIST 50	128	01.11.2016 – 30.04.2017	28
Blankespoor et al. (2014)	– number of followers – number of tweets (since account inception) – date of each firm's first tweet – number of months between the firm's first and last tweet – per-firm monthly average, percentage retweets – percentage replies, percentage links	IT companies from BusinessWeek's 2009 InfoTech Fortune's 20, Computer Business Review's Top Technology Firms, Net Valley's Top 100	4,516	04.03.2007 - 26.09.2009	85
Cole et al. (2015)	– number of tweets – months on twitter	S&P500	38,275	01.12.2010 - 31.12.2011	215
Guindy (2021)	– number of tweets produced by a firm – the number of tweeting days – and the number of words contained in tweets – number of retweets	NYSE, AMEX, NASDAQ	16,378	01.01.2006- 31.12.2018201 1-2015	864
Liu, Wu, Yu, Li and Lin (2013) and Liu et al. (2015)	– official twitter account – number of tweets – number of accounts a firm is following	NYSE, NASDAQ	11,034	01.01.2008 – 31.12.2012	293
Prokofieva (2015)	– number of tweets – number of retweets	S&P/ASX 200	3,516	01.08.2013 – 01.01.2014	109
Rakowski et al. (2017)	– number of tweets – increase in number of followers – increase in number of tweets	Russel 3000	2,215,535	01.01.2011 - 31.12.201501. 11.2016 – 30.04.2017	1,976
Ranco et al. (2015)	– financial tweets posted on Twitter – volume of tweets (daily) – number of negative tweets in a day, number of neutral tweets in a day, number of positive tweets in a day – sentiment polarity	DJIA30	1,555,770	1.06.2013 - 18.09.2014	30
Zhang et al. (2011)	– number of tweets per day – number of followers per day – number of retweets per day – positive and negative mood of the masses on Twitter	Dow Jones, NASDAQ, S&P 500	Ranging from 8,100 to 43,040 tweets per day	30.03.2009 - 07.09.2009	n/a

Source: authors' own compilation

The Capital Asset Pricing Model (CAPM) based on Sharpe (1964) and Lintner (1965) is used for risk–return evaluations for each portfolio:

$$E_{R_i} = R_f + \beta_{im}\big(E(R_m) - R_f\big), i = 1,2, \dots, n \qquad \text{Eq. (1)}$$

where:

$E(R_m)$ - the expected return of the market portfolio,

$E_{(Ri)}$ - the expected return of asset i (portfolio),

$E(R_m)$ - R_f - risk premium,

β_{im} - the risk of covariance of asset i (portfolio) in portfolio m (Fama & French, 2003),

R_f – risk-free interest rate.

According to Sharpe–Lintner CAPM the expected value of an asset's (portfolio) excess return (the asset's return minus the risk-free interest rate, $(R_{it}) - (R_{ft})$) is entirely explained by the expected CAPM risk premium ($\beta_i(E(R_{mt}) - R_{ft})$). Thus the "Jensen's Alpha", the constant term for each asset (portfolio), should be equal to zero in the time-series regression (Fama & French, 2004):

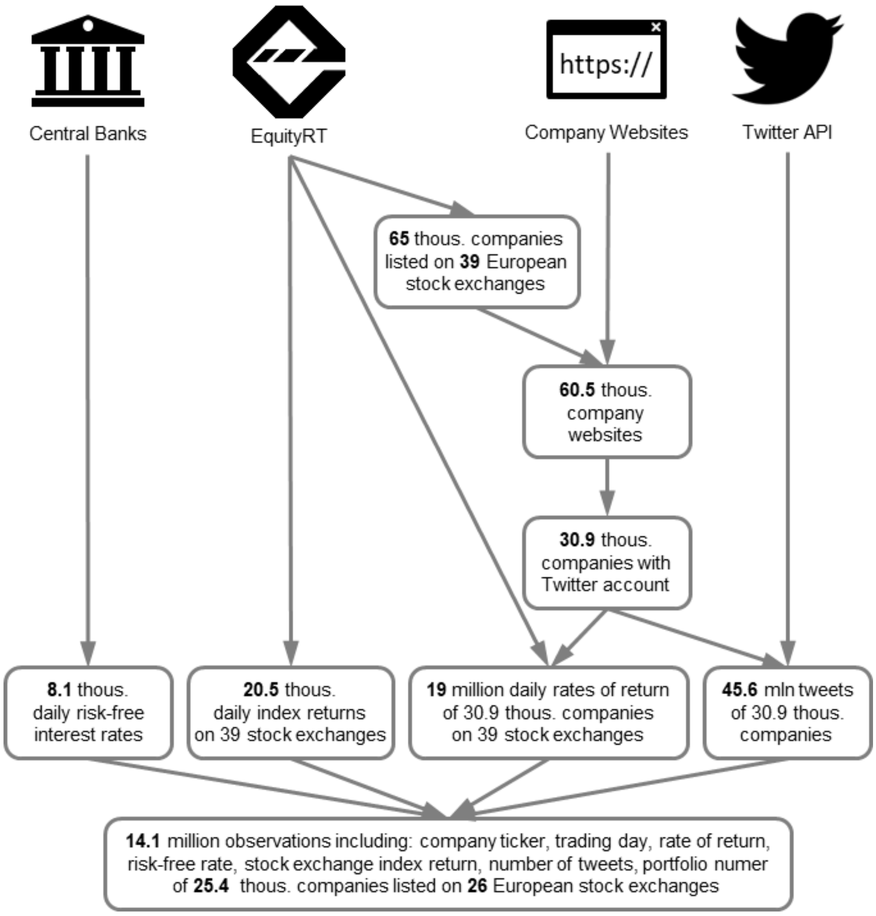
$$R_{it} - R_{ft} = \alpha_i + \beta_{im}\big(R_{mt} - R_{ft}\big) + \varepsilon_{it} \qquad \text{Eq. (2)}$$

As stated in Jensen (1968), if the Sharpe–Lintner risk–return relationship in Eq. (2) holds, the constant term in the time-series regression of the "excess" return on asset (portfolio) on the excess market return is zero for all assets (portfolios) (Fama & French, 2003). And as a result, the constant (Jensen's Alpha) in the time-series regression of the portfolio measures abnormal performance (Fama & French, 2003). In this analysis, the daily change of the local Interbank Offer Rate is used as the risk-free interest rate (Rf) and the daily change rate of the local index is used as market portfolio return (Rm). Detailed list of all the indices and risk-free rates sources is shown in Appendix 1.

We cover more than 65 thousand public companies, of which 47.3% are active on Twitter. Since there is no database that would list the names of Twitter accounts of European listed companies, we had to design a program to scrap this data from companies' websites. For this purpose, we used Selenium IDE tool to create a program in Python language. Then RStudio and package rtweet 0.7.0 were employed to collect information from Twitter. Rtweet helped us to gather and order information from Twitter by means of the Twitter Search API - approach commonly used in previous studies (e.g. Ranco et al. (2015)). Based on all the gathered data (tweets, stock indices, company quotes, risk-free rates) we created an SQL database. Finally, for each trading day we sorted the stocks into four equal portfolios for each stock exchange separately and verified the hypotheses.

Individual stages of the data processing are presented in Figure 1.

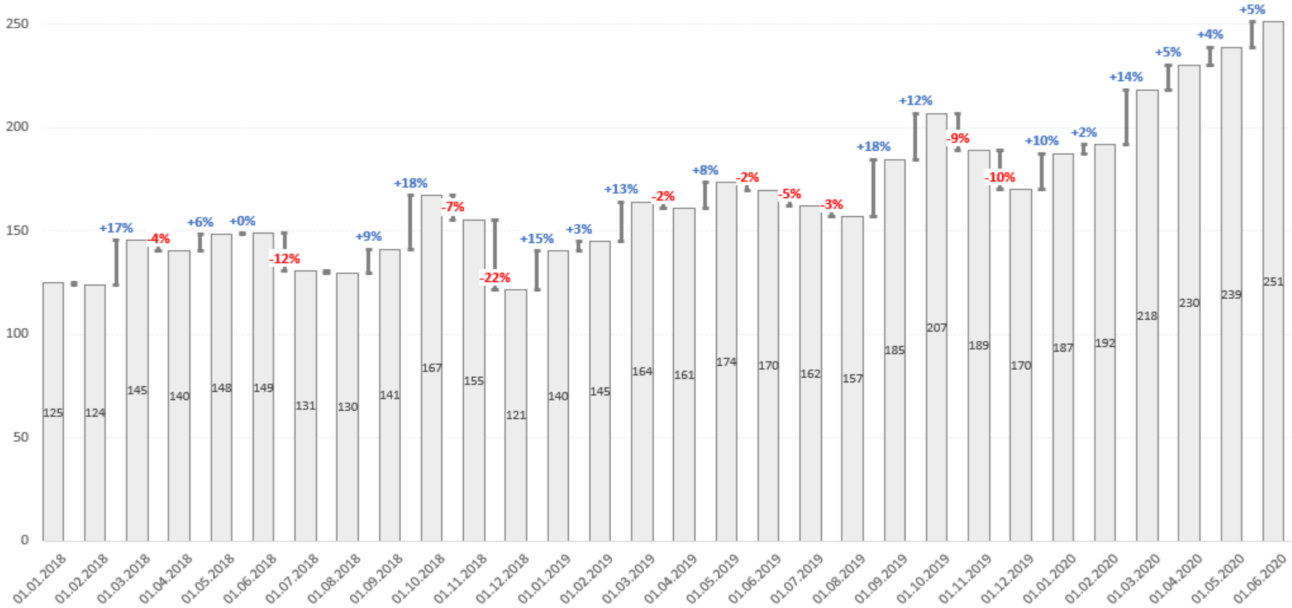
Figure 1. Summary of database development stages



Source: authors' own compilation.

Ultimately, the database comprises 45,566,846 tweets posted by 30,928 companies listed on 39 European stock exchanges.[3] German stock markets represent the largest percentage of the sample (74.1%). Figure 2 shows the number of tweets by companies in the sample. A steady increase in the number of tweets and tweeting companies is observed from the beginning of 2020 (Figure 2 and 3), especially in Northern Europe (Figure 4). The reason behind this is most probably the spread of the COVID-19 pandemic and the resulting implementation of remote solutions for working and also the rise of significance of online services.

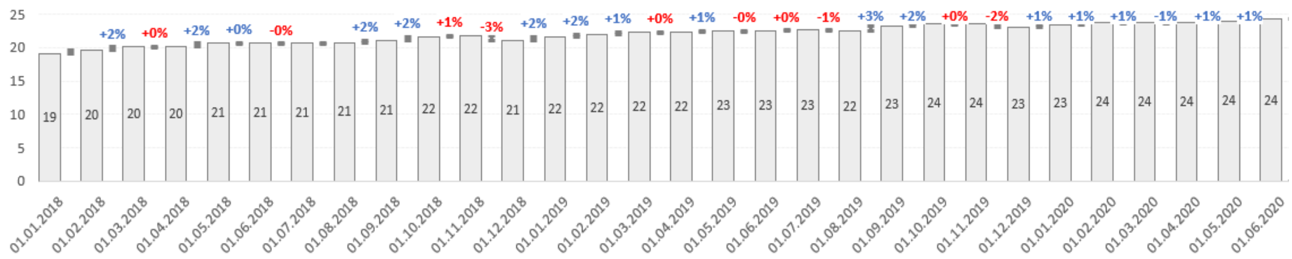
Figure 2. Number of tweets posted between January 2018 and June 2020 (in thousands) in the sample



Source: authors' own compilation

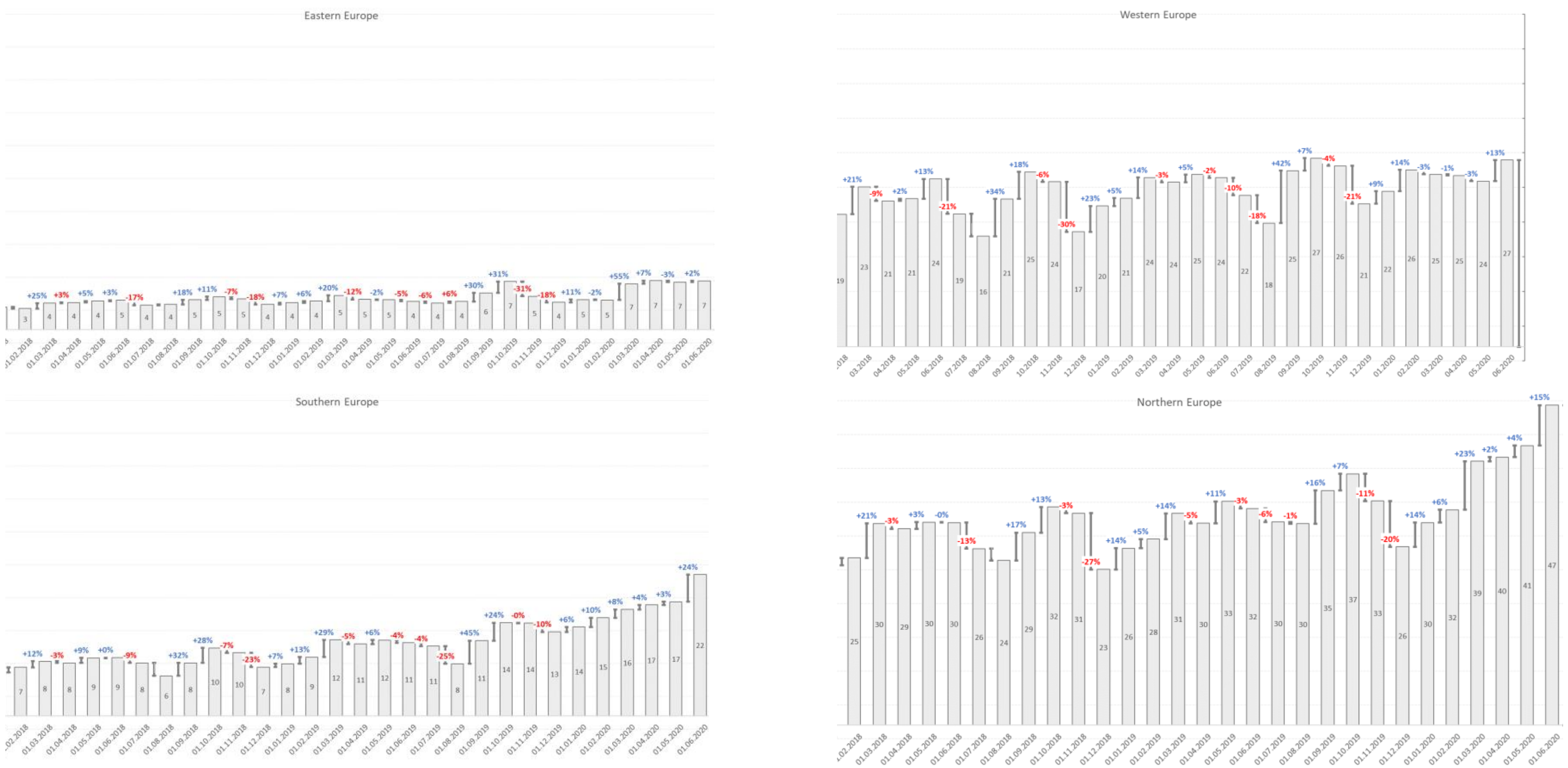
[3] In the case of companies listed on a few stock exchanges at the same time and with no Twitter accounts dedicated to the stock exchange, the company's official Twitter account was taken. This means that tweets posted from the official Twitter account are duplicated for those stock exchanges and a response to a tweet posted from a global account may be different on each of the markets on which the company was listed

Figure 3 Number of companies (in thousands) tweeting between January 2018 and June 2020



Source: authors' own compilation

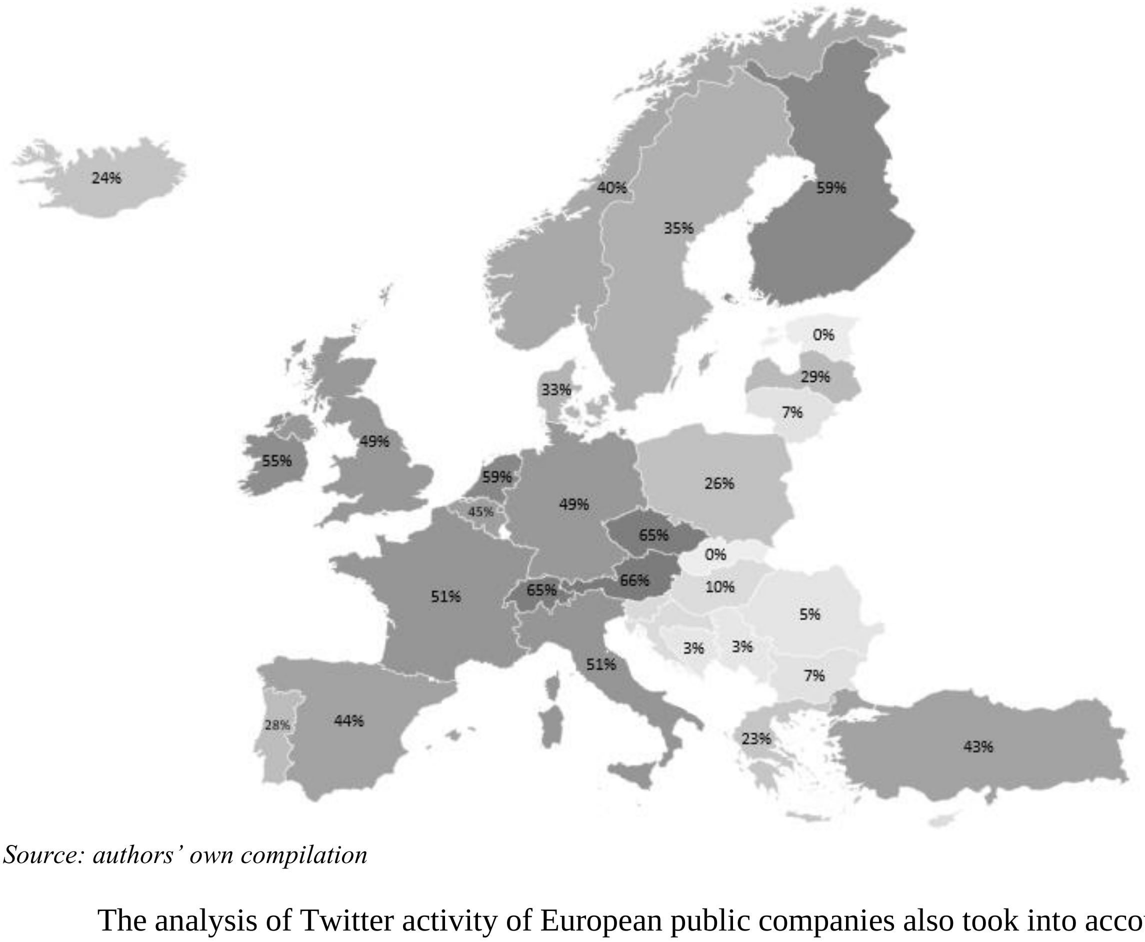
Figure 4. Number of tweets posted between January 2018 and June 2020 (in thousands) by region of Europe



Source: authors' own compilation. UN's grouping of European countries. Tweets have been divided by the company country of incorporation into one of the four areas of Europe in accordance with the United Nations classification.

Companies from Austria (66.2%), Switzerland (65.1%) and the Czech Republic (64.8%) account for the largest share of companies active on Twitter[4]. The average ages of a Twitter account in these countries are 9.3, 9.0 and 8.75 years, respectively. Eastern European companies under the UN classification are markedly less active on social media than companies from other areas of Europe (Figure 5). Given the poorer technological development, social media in these regions are not the investors' major communication channel and are not commonly used yet. On the other hand, countries of Northern and Western Europe use social media actively to acquire and build long-lasting business relations.

Figure 5. Share of companies active on Twitter in the total number of listed companies of a given market



Source: authors' own compilation

The analysis of Twitter activity of European public companies also took into account the date and month of the posts. Table 2 presents the share of information posted on individual days

[4] No company listed in Estonia and Slovakia had a Twitter account or provided a relevant link on their website

of the week and in individual months. The light (respectively dark) color indicates weak (respectively strong) intensity of tweet-posting.

Table 2 Activity on individual days of the week and in individual months

	January	February	March	April	May	June	July	August	September	October	November	December	
Monday	1.43%	1.53%	1.81%	1.85%	1.59%	2.01%	1.15%	0.89%	1.17%	1.24%	1.12%	1.18%	16.97%
Tuesday	1.70%	1.66%	1.90%	1.96%	2.00%	2.20%	1.21%	0.94%	1.16%	1.53%	1.22%	1.09%	18.57%
Wednesday	1.81%	1.72%	1.76%	2.08%	2.20%	2.01%	1.11%	1.06%	1.19%	1.55%	1.25%	0.96%	18.70%
Thursday	1.77%	1.76%	2.01%	2.07%	2.18%	2.00%	0.98%	1.20%	1.22%	1.44%	1.32%	0.99%	18.94%
Friday	1.52%	1.54%	1.87%	1.61%	2.02%	1.89%	0.87%	1.11%	1.06%	1.08%	1.29%	0.92%	16.78%
Saturday	0.42%	0.53%	0.60%	0.54%	0.64%	0.68%	0.26%	0.29%	0.36%	0.33%	0.38%	0.34%	5.37%
Sunday	0.37%	0.42%	0.57%	0.48%	0.55%	0.57%	0.25%	0.22%	0.34%	0.29%	0.28%	0.33%	4.67%
	9.02%	9.16%	10.52%	10.59%	11.18%	11.36%	5.83%	5.71%	6.50%	7.46%	6.86%	5.81%	100.00%

Source: authors' own compilation

Table 2 shows that social media activity was most intense in the pre-holiday season (June), between the second and fourth day of the week (Tuesday - Thursday). This coincides with the public company deadline for publishing periodical reports. This observation is consistent with results obtained by Hirshleifer et al. (2009). They document that investor inattention increases on days crowded with earnings announcements. We also find some evidence related to the well-known Monday effect. There is a large reduction in message posting activity on the first trading day of the week (Antweiler & Frank, 2004).

The next cross-section of the analysis focuses on the size of enterprises taken into account in the sample. Table 3 shows company Twitter activity broken down by capitalization rate (according to the EquityRT base classification). Active "Mega Cap" companies account for 83% of all companies in this group. This means that the larger the company, the greater the percentage of companies that have active Twitter accounts. This is in line with Alexander and Gentry's (2014) observations, who claim that the increasing transparency and accessibility also leads to an increase in customer communication, improved reputation, and greater market value. However, larger companies which are covered extensively by analysts, and companies that have a high percentage of institutional ownership may not always benefit from tweeting.

Table 3 The company Twitter activity broken down by capitalization rate

	Capitalization group	No. of companies (Total)	No. of companies with Twitter account (Active)	Active vs. Total %	Avg. tweets	Avg. followers
Micro Cap	< $50 million	17,499	5,526	31.58	529	140691890
Small Cap	between $50 million and $1 billion	20,854	8,944	42.89	957	620,343,078
Mid Cap	between $1 and $5 billion	12,345	6,346	51.41	1,596	395,733,417
Big Cap	between $5 and $75 billion	12,926	8,637	66.82	2,270	1,201,593,315
Mega Cap	> $75 billion	1,771	1,470	83.00	2,959	1026478491
n.d.	n.d	12	5	41.67		
		65,407	30,928	47.29	1,662	676,968,038

Source: authors' own compilation on the basis of EquityRT

According to Guindy (2021) smaller companies, with the least analyst followings, and with the least institutional holdings, are more likely to gain from tweeting financial information, precisely because they lack alternative sources of coverage, and thus Twitter can emerge as a substitute information source. Table 4 presents the company Twitter activity broken down by capitalization rate and stock exchange. The light (respectively dark) color indicates weak (respectively strong) intensity of tweet-posting.

Table 4 Daily average number of tweets by stock exchange and company size

Exchange	1 Micro Cap	2 Small Cap	3 Mid Cap	4 Big Cap	5 Mega Cap	Total
AktieTorget Stock Exchange	0,79	1,77	2,86			**1,00**
Borsa Istanbul	0,87	1,59	2,81	1,43		**1,47**
Oslo Stock Exchange	0,76	1,33	2,36	2,73		**1,58**
Nasdaq OMX Stockholm	1,18	1,21	2,79	2,87		**1,74**
Warsaw Stock Exchange	1,05	2,15	3,76	5,56		**1,95**
Irish Stock Exchange	1,26	1,77	2,85	3,38		**2,19**
Athens Stock Exchange	0,41	3,97	3,59	6,40		**2,24**
Nasdaq OMX Copenhagen	3,21	1,33	2,60	2,45	3,58	**2,54**
Nasdaq OMX Helsinki	1,63	2,12	2,98	4,48		**2,61**
Euronext Paris	1,60	2,10	2,91	5,15	5,75	**2,68**
Frankfurt Stock Exchange	1,23	2,12	3,28	4,11	5,48	**2,87**
Berlin-Bremen Stock Exchange	1,17	2,09	3,28	4,27	5,50	**2,91**
Stuttgart Stock Exchange	1,25	2,08	3,17	4,19	5,46	**2,92**
London Stock Exchange	1,54	2,14	3,19	4,13	5,87	**2,98**
Brussels Stock Exchange	3,14	0,62	2,17	4,02	6,71	**3,00**
Amsterdam Stock Exchange	0,96	1,53	1,40	3,65	6,62	**3,12**
Munich Stock Exchange	1,23	2,22	3,59	4,29	5,43	**3,30**
Madrid Stock Exchange	2,12	2,08	3,97	6,13	4,43	**3,45**
Hamburg Stock Exchange	0,89	1,77	3,05	4,53	5,40	**3,52**
Borsa Italiana	2,15	1,99	3,73	4,91	5,34	**3,53**
Dusseldorf Stock Exchange	1,07	2,08	3,51	4,28	5,67	**3,75**
Xetra	0,82	1,90	3,57	4,66	5,82	**3,94**
SIX Swiss Exchange	2,94	1,87	3,20	4,39	5,98	**3,98**
Hannover Stock Exchange	1,39	2,13	3,55	4,78	5,76	**4,51**
Vienna Stock Exchange	0,96	2,67	3,49	4,91	6,03	**4,67**
Prague Stock Exchange		2,91	4,15	5,55	8,13	**5,04**
Total	**1,27**	**2,08**	**3,29**	**4,29**	**5,65**	**3,10**

Source: authors' own compilation

Table 4 shows that companies in Germany are even more active than the ones listed in the United Kingdom. The same applies to the Dutch ones. We also carry out a cross-analysis of tweets posted, respecting the breakdown according to capitalization referred to above (Appendix 2). Each group record a higher number of tweets month after month. It is worth emphasizing that the lowest dynamics are seen in the "Micro Cap" and "Mega Cap" groups.

Sectoral affiliation (Table 5) was another attribute taken into account in the analysis. The majority of cases fall under the Medical care sector (4,435 companies). However, the most active companies come from the Computer Software & Services sector (6,736,344 tweets). The research period covered the period January 2018-June 2020 during which the significance of this industry grew markedly in the global economy. According to Gartner the global IT market in 2012-2019 grew on average 3.4 per cent per year, though majority of this growth fell over the later part of the period (Gartner, 2020). Moreover, 2020 marked the beginning of the COVID-19 lockdowns and the resulting economic disruptions. The IT sector companies were one of the few that did not experience adverse effects of that situation. Guindy (2021) draws similar conclusions. Computer services and entertainment tend to tweet more, whereas industries such as steelworks and mining are industries that tweet the least. Customer Services also stands out against the others where the number of Twitter-active companies in this sector and the average number of tweets posted is below average for the entire population, but messages posted by companies from this sector have the most followers - more than 766 million people. We may assume that this is down to the nature of the information posted. Sporting and music events are one of the most popular subjects on Twitter. Companies that operate in this industry use social networking sites for marketing purposes.

Table 5 Company activity on Twitter broken down by sector (industry)

Security Industry Name	*No of. companies (Total)*	*No. of company with Twitter profile (Active)*	*Active vs. Total (%)*	*Tweets*	*Avg. tweets*	*Avg. followers*
Real Estate	3,430	875	25.51	815,212	931.67	8,593,324.96
Materials	1,234	403	32.66	381,378	946.35	2,126,182.41
Engineering & Construction	2,014	700	34.76	966,219	1,380.31	11,357,381.27
Financial Services	3,252	1,162	35.73	1,856,824	1,597.96	77,992,139.43
Consumer Products	2,885	1,084	37.57	1,861,359	1,717.12	47,556,506.15
Energy	4,154	1,586	38.18	1,738,145	1,095.93	74,261,834.47
Textile & Apparel	1,016	393	38.68	596,832	1,518.66	441,935,262.13
Consumer Durables	784	320	40.82	500,937	1,565.43	31,329,242.88
Consumer Services	2,395	1,021	42.63	1,992,818	1,951.83	766,175,527.55
Metals & Mining	6,703	2,874	42.88	1,753,093	609.98	23,656,383.54
Transportation & Logistics	1,776	808	45.50	1,361,776	1,685.37	61,538,940.82
Industrial Goods & Services	4,477	2,051	45.81	2,646,173	1,290.19	74,582,752.03
Retail	2,388	1,122	46.98	2,064,125	1,839.68	268,910,986.88
Chemicals	1,534	730	47.59	913,064	1,250.77	11,604,455.55
Automotive & Truck Manufacturing	1,456	717	49.24	1,174,446	1,638.00	155,910,151.47
Utilities	1,772	894	50.45	1,557,162	1,741.79	18,779,668.99
Media & Marketing	2,308	1,203	52.12	2,122,554	1,764.38	225,583,500.90
Commercial Services	1,462	793	54.24	1,289,008	1,625.48	9,807,654.81
Medical Care	8,154	4,435	54.39	4,310,199	971.86	116,553,901.56
IT Hardware & Electronics	2,255	1,296	57.47	1,960,256	1,512.54	127,339,891.78
Insurance	1,072	617	57.56	1,356,725	2,198.91	44,412,331.28
Banking	2,422	1,417	58.51	2,942,600	2,076.64	220,349,445.09
Communication Services	1,981	1,243	62.75	2,669,597	2,147.70	172,025,441.04
Computer Software & Services	4,483	3,184	71.02	6,736,344	2,115.69	392,456,285.35
Total	**65,407**	**30,928**	**47.29**	**45,566,846.00**	**1,548.93**	**3,384,839,192.33**

Source: authors' own compilation

We also carry out a cross-analysis of tweets posted, respecting the breakdown according to capitalization and sector (Table 6). The light (respectively dark) color indicates weak (respectively strong) intensity of tweet-posting.

Table 6. Daily average number of tweets by sector (industry) and company size

Security Industry Name	1 Micro Cap	2 Small Cap	3 Mid Cap	4 Big Cap	5 Mega Cap	Total
Metals & Mining	0,87	1,00	1,76	2,74	3,25	**1,33**
Materials	0,98	1,82	1,81	2,57		**1,99**
Medical Care	0,95	1,13	1,82	3,46	5,42	**2,03**
Real Estate	1,66	1,69	2,07	2,50	2,87	**2,08**
Energy	0,92	1,29	1,78	3,50	4,42	**2,15**
Chemicals	1,19	0,88	2,05	3,42	2,01	**2,45**
Industrial Goods & Services	0,77	1,44	2,31	3,61	7,01	**2,71**
Engineering & Construction	1,55	2,19	3,26	3,94		**2,98**
Automotive & Truck Manufacturing	0,72	1,20	2,41	4,70	4,05	**3,13**
IT Hardware & Electronics	1,29	1,75	4,05	3,98	4,31	**3,13**
Textile & Apparel	1,21	1,75	3,51	4,02	5,70	**3,29**
Consumer Durables	2,39	2,15	4,71	5,38	8,23	**3,42**
Financial Services	2,19	2,27	3,50	4,20	5,76	**3,46**
Utilities	1,08	1,31	2,72	4,79	5,52	**3,56**
Consumer Products	1,42	2,60	3,52	3,32	6,38	**3,68**
Commercial Services	1,62	2,95	3,83	5,16	8,15	**3,70**
Transportation & Logistics	2,37	2,67	3,62	4,86	3,06	**3,74**
Media & Marketing	1,81	3,08	4,86	5,63	2,84	**3,89**
Insurance	0,89	2,64	3,26	4,22	4,37	**3,94**
Retail	2,68	4,16	4,49	3,34	6,49	**3,95**
Computer Software & Services	1,46	3,23	5,11	6,44	8,36	**4,21**
Consumer Services	2,54	3,66	4,69	5,20	5,26	**4,21**
Communication Services	1,62	3,33	4,66	5,27	6,33	**4,33**
Banking	1,57	2,63	4,28	5,62	5,45	**4,59**
Total	**1,27**	**2,08**	**3,29**	**4,29**	**5,65**	**3,10**

Source: authors' own compilation

Mega companies in Computer Software & Services, Consumer Durables and Commercial services sector were the most active ones between January 2018 and June 2020. When we analyzed data for each sector separately, we found out that medical care sector twitter activity decreased significantly during the pandemic period.

4. Results

We identify 39 stock markets for which information was available in order to build a CAPM model (rates of return, stock market index and risk-free rate of return for a given country). Then, the number of companies tweeting on each trading day in the given period was verified (from January 2018 to June 2020). For a given market to qualify for further analysis, a minimum of 20 companies had to post one tweet on each trading day (Table 7)[5]. This criterion eliminated 13 stock exchanges from the sample.

Table 7 Classification of data to the population investigated

No.	Division of Europe according to UN.	Market	Minimum number	Maximum number	Days with more than 20 companies
1.	Southern	Italy Borsa Italiana	163	214	623
2.	Southern	Spain Madrid SE	94	121	623
3.	Southern	Turkey Borsa Istanbul	57	65	623
4.	Southern	Greece: Athens SE	23	33	623
5.	Southern	Serbia: Belgrade SE	13	13	0
6.	Southern	Portugal: Lisbon SE	11	15	0
7.	Southern	Malta: Malta SE	7	8	0
8.	Southern	Bosnia and Herzegovina Banja Luka SE	7	7	0
9.	Southern	Slovenia: Ljubljana SE	5	5	0
10.	Southern	Cyprus: Cyprus SE:	3	10	0
11.	Southern	Croatia: Zagreb SE	3	13	0
12.	Northern	Sweden: Nasdaq OMX Stockholm	197	256	623
13.	Northern	Finland: Nasdaq OMX Helsinki	79	95	623
14.	Northern	Norway: Oslo SE	62	75	623
15.	Northern	Denmark: Nasdaq OMX Copenhagen	38	46	623
16.	Northern	Sweden: AktieTorget SE / Spotlight SE	26	41	623
17.	Northern	Ireland: Irish SE	21	26	623
18.	Northern	Latvia: Nasdaq OMX Riga	3	4	0
19.	Northern	Iceland: Nasdaq OMX Iceland	2	6	0
20.	Eastern	Poland: Warsaw SE	1	170	622
21.	Eastern	Czech Republic: Prague SE	8	32	523
22.	Eastern	Bulgaria: Bulgarian SE	2	5	0
23.	Eastern	Romania: Bucharest SE	2	2	0
24.	Eastern	Hungary: Budapest SE	2	2	0
25.	Eastern	Lithuania: Nasdaq OMX Vilnius	1	1	0
26.	Western	Germany: Stuttgart SE	2,889	4,255	623
27.	Western	Germany: Frankfurt SE	2,290	5,097	623
28.	Northern	Great Britain: London SE	1,303	2,879	623
29.	Western	Germany: Berlin-Bremen SE	1,015	4,092	623
30.	Western	Germany: Munich SE	453	2,786	623
31.	Western	Germany: Xetra	426	772	623
32.	Western	France: Euronext Paris	318	401	623
33.	Western	Germany: Hamburg SE	135	717	623
34.	Western	Germany: Dusseldorf SE	107	1,744	623
35.	Western	The Netherlands: Amsterdam SE	58	82	623
36.	Western	Belgium: Brussels SE	51	77	623
37.	Western	Switzerland: SIX Swiss Exchange	493	515	622
38.	Western	Germany: Hannover SE	43	337	623
39.	Western	Austria: Vienna SE	19	496	622

Source: authors' own compilation. Markets not qualified for the research are marked in red. SE abbreviation: Stock Exchange

[5] Each of the four portfolios had to have at least 5 financial instruments.

The portfolio sorting method was used to test the research hypotheses. The CAPM model parameters were assessed on the basis of the ordinary least squares method (OLS). The dependent variable is the difference between the rate of return on the company's stocks and the risk-free rate of return for a given capital market, while the independent variable is the difference between the market rate of return and the risk-free rate of return. The regression analysis was conducted for 26 stock exchanges, that is, 25,424 companies and the corresponding 6,044 active Twitter accounts. Descriptive statistics were generated for each of the four portfolios for each market (a total of 104 portfolios). The company's activity level was measured on the basis of the number of tweets posted by the company on a given trading day. Portfolios were sorted according to the decreasing number of tweets (Portfolio 1 - the most active companies, Portfolio 4 - the least active companies). The average daily number of tweets, average daily number of companies and average rates of return for each is shown in Table 8.

The average rate of return on portfolio 1 is less negative compared to portfolios of companies that show lesser Twitter activity. This may indicate that the mere interest in the public sphere is enough to affect stock prices, even if information published does not have new or previously unknown content (Lee et al., 2021). The results presented in this paper suggest that Twitter activity causes increased recognition and thus the companies' increased attractiveness in the eyes of the investors. In the majority of cases, the average rate of return in portfolio 1 (most active companies) is higher than those obtained by other stock portfolios.

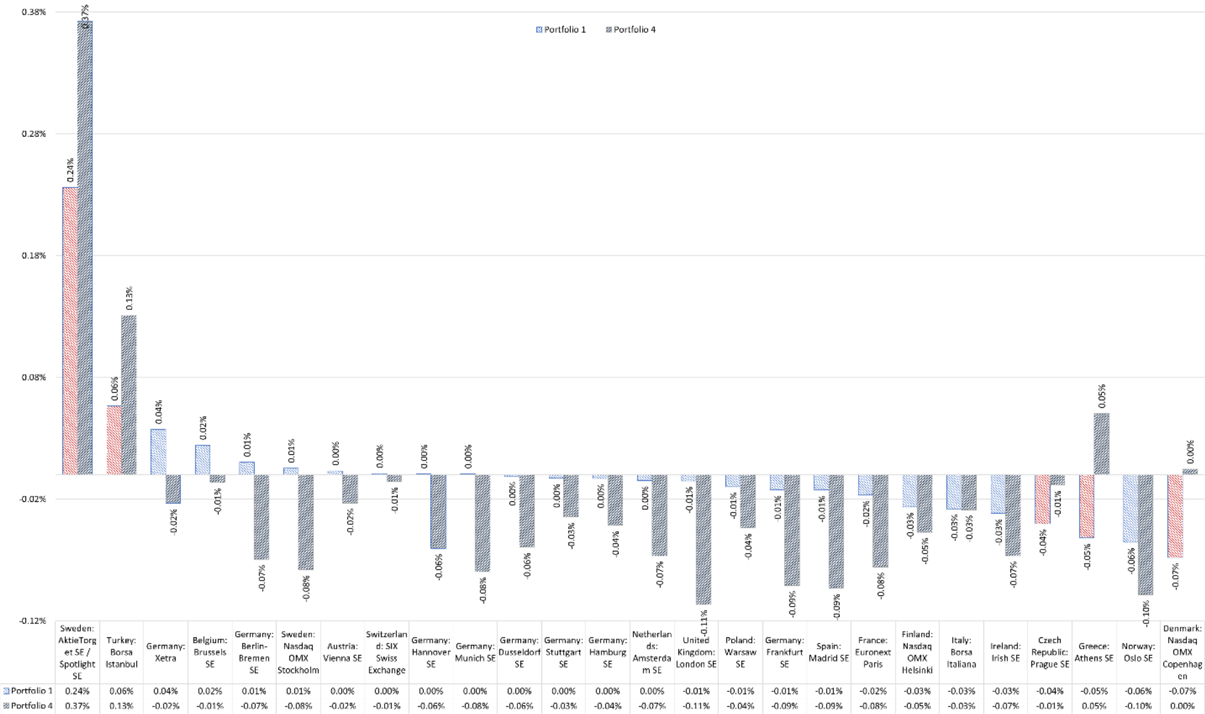
Table 8 Average values in portfolios for individual capital markets

Portfolio no.	*Average number of tweets* 1	2	3	4	Average rates of return (%) 1	2	3	4	*Average number of companies* 1	2	3	4
Sweden: AktieTorget SE / Spotlight SE	3.57	0.34	0	0	0.24%	-0.03%	-0.64%	0.37%	8.87	8.79	8.76	8.34
Turkey Borsa Istanbul	4.62	1.05	0.12	0	0.06%	0.13%	0.00%	0.13%	15.67	15.43	15.36	15.1
Germany: Xetra	11.95	3.02	0.77	0	0.04%	0.01%	0.01%	-0.02%	184.25	184.02	183.7	183.49
Belgium: Brussels SE	10.15	1.5	0.11	0	0.02%	-0.06%	-0.09%	-0.01%	19.2	18.67	18.62	18.54
Germany: Berlin-Bremen SE	9.52	1.86	0.24	0	0.01%	-0.02%	-0.07%	-0.07%	960.32	960.04	959.74	959.53
Sweden: Nasdaq OMX Stockholm	5.82	1.06	0.03	0	0.01%	-0.01%	-0.06%	-0.08%	61.28	60.96	60.8	60.56
Austria: Vienna SE	13.98	3.6	1.05	0.02	0.00%	0.00%	-0.03%	-0.02%	105.75	105.61	105.42	105.07
Germany: Stuttgart SE	12.77	3.81	1.33	0.06	0.00%	-0.01%	-0.01%	-0.03%	960.49	960.25	960.01	959.74
Switzerland: SIX Swiss Exchange	11.73	3.17	0.97	0.01	0.00%	0.02%	-0.01%	-0.01%	127.16	126.96	126.83	126.48
Germany: Dusseldorf SE	11.69	2.71	0.59	0	0.00%	-0.03%	-0.02%	-0.06%	337	336.79	336.57	336.21
Germany: Hamburg SE	10.99	2.53	0.54	0	0.00%	-0.01%	-0.03%	-0.04%	170.39	170.14	169.9	169.6
Germany: Hannover SE	10.64	2.2	0.36	0	0.00%	-0.03%	-0.06%	-0.06%	80.73	80.63	80.36	79.99
The Netherlands: Amsterdam SE	10.4	1.69	0.18	0	0.00%	-0.03%	-0.01%	-0.07%	20.31	20.06	19.81	19.36
Germany: Munich SE	9.57	1.87	0.25	0	0.00%	-0.02%	-0.08%	-0.08%	600.59	600.29	600.07	599.83
Spain: Madrid SE	10.95	2.34	0.36	0	-0.01%	-0.06%	-0.06%	-0.09%	29.92	29.63	29.55	29.03
Great Britain: London SE	9.64	1.98	0.28	0	-0.01%	-0.02%	-0.03%	-0.11%	694.62	694.4	694.15	693.86
Germany: Frankfurt SE	9.39	1.84	0.23	0	-0.01%	-0.03%	-0.09%	-0.09%	1190.3	1190.04	1189.82	1189.58
Poland: Warsaw SE	6.81	0.91	0	0	-0.01%	-0.02%	-0.07%	-0.04%	40.86	40.48	40.33	40.24
France: Euronext Paris	8.57	1.87	0.23	0	-0.02%	-0.02%	-0.12%	-0.08%	98.26	97.77	97.58	97.44
Italy: Borsa Italiana	11.21	2.4	0.43	0	-0.03%	-0.04%	-0.06%	-0.03%	15.67	15.43	15.36	15.1
Finland: Nasdaq OMX Helsinki	7.94	1.95	0.45	0	-0.03%	-0.05%	-0.03%	-0.05%	22.96	22.74	22.55	22.36
Ireland: Irish SE	7.24	0.87	0.02	0	-0.03%	-0.02%	-0.08%	-0.07%	6.92	6.63	6	6
Cz. Rep.: Prague SE	14.85	3.47	0.77	0.01	-0.04%	-0.04%	-0.03%	-0.01%	7.91	7.83	7.1	6.97
Greece: Athens SE	7.79	0.48	0	0	-0.05%	-0.01%	0.05%	0.05%	8.99	8	8	7.99
Norway: Oslo SE	5.11	1.02	0.07	0	-0.06%	-0.06%	-0.08%	-0.10%	18.59	18.3	18.25	17.65
Denmark: Nasdaq OMX Copenhagen	8.28	1.38	0.11	0	-0.07%	0.05%	0.00%	0.00%	11.81	11.73	11	10.9
Total average	**9.43**	**1.96**	**0.37**	**0.00**	**0.00%**	**-0.02%**	**-0.07%**	**-0.03%**	**223.03**	**222.75**	**222.52**	**222.27**

Source: authors' own compilation. Data sorted according to the declining rate of return in portfolio 1. Portfolios for which the average rate of return in portfolio 1 (most active companies) is lower than those obtained by the other stock portfolios are marked in red. SE abbreviation: Stock Exchange.

The next stage of the analysis of the link between Twitter activity and the market valuation of European listed companies was to examine the differences in average rates of return for extreme portfolios of a given population (Figure 6). We note that losses generated by portfolio 1 are smaller than those generated by portfolio 4, which features low Twitter activity. This observation may be crucial for building investment strategies.

Figure 6 Average rates of return in portfolio 1 and portfolio 4



Source: authors' own compilation. Portfolios for which the average rate of return in portfolio 1 (most active companies) is lower than those obtained by the other stock portfolios are marked in red. SE abbreviation: Stock Exchange.

Table 9 shows the results of a regression analysis of portfolios, constructed on the basis of the disclosure measure (number of tweets posted by a company), based on Sharpe's (1964) and Lintner's (1965) CAPM.

CAPM regression results for most of the portfolios, generated according to the given metric, have statistically significant alphas. This signals that better Twitter performance results in significant increases in shareholder abnormal returns. It is particularly noteworthy that portfolios with a high number of tweets have significant alphas. For all Western European markets the hypothesis that Twitter activity affects the stock market value (alpha is statistically significant) has been confirmed.

This result coincides with the findings of the market betas, which are significant and higher in portfolio 1 than in portfolio 4. We observe that portfolios with a high number of tweets posted by a company are riskier than alternative portfolios. Therefore, portfolio returns with superior Twitter performance in related metrics are more sensitive to changes in market returns (Fama & French, 2003).

Table 9 Results of regression for portfolios from each capital market

Country: stock exchange	*n*	*α1*	*β1*	*Adj R^2 (%)*	*α2*	*β2*	*Adj R^2 (%)*	*α3*	*β3*	*Adj R^2 (%)*	*α4*	*β4*	*Adj R^2 (%)*
Austria: Vienna SE	600	0.001 -0.000 ***	0.312 - 0.017 ***	37.1	0.001 -0.000 ***	0.312 - 0.014 ***	44.4	0.001 - 0.000 **	0.314 - 0.014 ***	45.5	0.001 - 0.000 ***	0.294 0.014 ***	41.4
Belgium: Brussels SE	612	0.001 -0.000 ***	0.472 - 0.017 ***	55.2	0.000 0.000	0.526 - 0.021 ***	51.5	0.000 0.000	0.458 - 0.017 ***	55.2	0.000 0.000	0.463 - 0.019 ***	50.7
Switzerland: SIX Swiss Exchange	591	0.002 -0.000 ***	0.181 - 0.012 ***	27.6	0.002 - 0.000 ***	0.228 - 0.011 ***	42.3	0.001 - 0.000 ***	0.236 - 0.010 ***	49.6	0.002 - 0.000 ***	0.230 - 0.011 ***	42.3
Cz. Rep.: Prague SE	505	-0.002 -0.000 ***	0.644 - 0.029 ***	49.5	- 0.002 - 0.000 ***	0.611 - 0.025 ***	54.7	- 0.002 - 0.000 ***	0.624 - 0.024 ***	58.2	- 0.002 - 0.000 ***	0.538 - 0.029 ***	41.2
Germany: Berlin -Bremen SE	604	0.001 -0.000 ***	0.371 - 0.012 ***	62.6	0.001 - 0.000 ***	0.335 - 0.011 ***	58.6	0.000 0.000	0.320 - 0.012 ***	54	0.000 0.000	0.312 - 0.012 ***	51.3
Germany: Dusseldorf SE	604	0.001 -0.000 *	0.616 - 0.017 ***	69.3	0.000 0.000	0.574 - 0.016 ***	67.3	0.000 0.000	0.558 - 0.016 ***	67.1	0.000 0.000	0.559 - 0.017 ***	65.4
Germany: Frankfurt SE	604	0.001 -0.000 *	0.492 - 0.014 ***	66	0.000 0.000	0.468 - 0.015 ***	60.7	- 0.000 0.000	0.431 - 0.017 ***	51.4	- 0.000 0.000	0.412 - 0.018 ***	46.5
Germany: Hamburg SE	604	0.001 -0.000 ***	0.269 - 0.011 ***	49.8	0.001 - 0.000 ***	0.255 - 0.010 ***	53.1	0.001 - 0.000 ***	0.214 - 0.010 ***	42.9	0.000 - 0.000 **	0.177 - 0.010 ***	32.1
Germany: Hannover SE	604	0.001 -0.000 ***	0.242 - 0.009 ***	52.6	0.001 - 0.000 ***	0.206 - 0.011 ***	38.9	0.001 - 0.000 ***	0.234 - 0.011 ***	43.2	0.001 - 0.000 **	0.214 - 0.013 ***	32.5
Germany: Munich SE	604	0.001 -0.000 ***	0.277 - 0.015 ***	36.5	0.001 - 0.000 **	0.258 - 0.015 ***	32.2	0.000 - 0.000	0.222 - 0.016 ***	23.9	0.000 0.000	0.203 - 0.016 ***	21.5
Germany: Stuttgart SE	604	0.000 -0.000	0.703 - 0.019 ***	69.8	0.000 - 0.000	0.673 - 0.021 ***	64.1	- 0.000 - 0.000	0.638 - 0.020 ***	63.2	- 0.000 - 0.000	0.627 - 0.020 ***	61.5
Germany: Xetra	604	0.001 -0.000	0.524 - 0.012 ***	77.4	0.001 - 0.000 ***	0.504 - 0.012 ***	74.5	0.001 - 0.000 ***	0.485 - 0.009 ***	82.3	0.000 - 0.000 **	0.459 - 0.011 ***	75.9
Denmark: Nasdaq OMX Copenhagen	592	-0.001 -0.000 **	0.908 - 0.037 ***	50.1	0.000 - 0.000	0.841 - 0.030 ***	57.3	- 0.000 - 0.000	0.819 - 0.030 ***	56.1	- 0.001 - 0.000	0.818 - 0.032 ***	52
Spain: Madrid SE	613	0.000 -0.000 *	0.734 - 0.017 ***	75.6	0.000 - 0.000	0.563 - 0.016 ***	65.9	0.000 - 0.000	0.573 - 0.018 ***	61.1	- 0.000 - 0.000	0.558 - 0.018 ***	61
Finland: Nasdaq OMX Helsinki	600	-0.000 -0.000	0.781 - 0.023 ***	65	- 0.000 - 0.000	0.740 - 0.024 ***	62.2	- 0.000 - 0.000	0.672 - 0.020 ***	66.1	0.000 - 0.000	0.638 - 0.020 ***	62.5
France: Euronext Paris	612	0.000 0.000 *	0.637 - 0.013 ***	79.5	0.000 - 0.000	0.633 - 0.016 ***	72	- 0.000 - 0.000	0.511 - 0.016 ***	62.3	- 0.000 - 0.000	0.491 - 0.017 ***	57.7
Great Britain: London SE	606	-0.001 -0.000 **	0.529 - 0.016 ***	64.1	- 0.001 - 0.000 ***	0.519 - 0.015 ***	65.1	- 0.001 - 0.000 ***	0.484 - 0.016 ***	60.6	- 0.001 - 0.000 ***	0.460 - 0.016 ***	57
Greece: Athens SE	593	-0.000 -0.000	0.907 - 0.029 ***	63.1	0.001 - 0.000 **	0.687 - 0.023 ***	59.9	0.001 - 0.000 **	0.596 - 0.021 ***	57.3	0.001 - 0.000 **	0.596 - 0.021 ***	57.2
Ireland: Irish SE	609	0.001 -0.000	0.094 - 0.024 ***	2.4	0.001 - 0.000 **	0.091 - 0.019 ***	3.5	0.000 - 0.000	0.081 - 0.025 **	1.7	0.000 - 0.000	0.079 - 0.025 **	1.6
Turkey: Borsa Istanbul	619	0.004 -0.001 ***	1.055 - 0.021 ***	80.3	0.002 - 0.001 *	1.010 - 0.019 ***	82.4	0.002 - 0.001	1.008 - 0.017 ****	84.5	0.002 - 0.001 *	1.016 - 0.018 ***	83.6
Italy: Borsa Italiana	609	0.000 -0.000	0.676 - 0.016 ***	74.5	0.000 - 0.000	0.664 - 0.013 ***	81.7	0.000 - 0.000	0.607 - 0.012 **	81.2	0.000 - 0.000	0.581 - 0.012 **	80.7
The Netherlands: Amsterdam SE	612	0.001 -0.000 ***	0.477 - 0.012 ***	71.2	0.000 - 0.000	0.833 - 0.018 ***	77.8	- 0.000 - 0.000	0.818 - 0.018 ***	77.6	- 0.000 - 0.000	0.805 - 0.019 ***	73.9
Norway: Oslo SE	598	-0.000 -0.000	0.964 - 0.022 ***	76.3	- 0.000 - 0.000	0.898 - 0.021 ***	74.8	- 0.001 - 0.000 *	0.913 - 0.021 **	75.4	- 0.001 - 0.000 *	0.919 - 0.023 **	73.5
Poland: Warsaw SE	596	-0.000 -0.000	0.797 - 0.020 ***	72.6	- 0.001 - 0.000 **	0.635 - 0.024 ***	54.2	- 0.002 - 0.000 ***	0.545 - 0.023 ***	49.1	- 0.002 - 0.000 ***	0.544 - 0.023 ***	49.1
Sweden: Nasdaq OMX Stockholm	601	0.000 -0.000	0.784 - 0.017 ***	78.4	- 0.000 - 0.000	0.830 - 0.019 ***	76.4	- 0.001 - 0.000 **	0.803 - 0.018 **	77.8	- 0.001 - 0.000 **	0.801 - 0.018 **	76.6
Sweden: AktieTorget SE / Spotlight SE	599	-0.001 -0.005	1.956 - 0.371 ***	4.4	0.000 - 0.003	1.092 - 0.276 ***	2.6	- 0.001 - 0.003	0.500 - 0.269	0.6	- 0.001 - 0.003	0.498 - 0.269	0.6

*Source: authors' own compilation. P-value given in brackets. *, **, *** mean significance at α =0.1; = 0.05 and = 0.01, respectively. SE abbreviation: Stock Exchange*

5. Conclusion

This paper makes use of a large novel data set comprising a record of the tweeting activity of all companies listed on European stocks exchanges from January 2018 to June 2020. We focus on the behavior of retail investors and seek an answer to the question whether social media can help companies reduce information asymmetry and increase rates of return.

CAPM regression results for most of the portfolios, generated according to the given metric, have statistically significant alphas. This signals that better Twitter performance results in significant increases in shareholder abnormal returns. We show that market betas in portfolio 1, with a high number of tweets, are higher than the betas in other portfolios. In other words, portfolio returns with higher Twitter performance are more sensitive to changes in market returns. These results are consistent with Guindy (2021). Also Jeon et al (2021) find that stock return jumps are significantly related to news flow frequency over the last few decades and that the sensitivity of jump probability to news is stronger for firms with higher media visibility.

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Appendix 1 Detailed list of all the indices and risk free rates sources

Division of Europe according to UN.	Country: Market	MIC	EquityRT Index Ticker	Risk Free Rate
Western	Austria: Vienna SE	XWBO	ATX:AT	EONIA
Western	Belgium: Brussels SE	XBRU	BELAS:BE	EONIA
Southern	Bosnia and Herzegovina: Banja Luka SE	BLSE	BIRS:BAL	EONIA
Eastern	Bulgaria: Bulgarian SE	XBUL	SOFIX:BG	LEONIA
Southern	Croatia: Zagreb SE	XZAG	CROBEX:HR	ZIBOR, EONIA
Southern	Cyprus: Cyprus SE:	XCYS	OMXIPI:IC	EONIA
Eastern	Czech Republic: Prague SE	XPRA	PXG:CZ	PRIBOR
Northern	Denmark: Nasdaq OMX Copenhagen	XCSE	OMXCPI:DK	DKK LIBOR, CIBOR
Northern	Estonia: Nasdaq OMX Tallinn	XTAL	OMXTGI:EE	EONIA
Northern	Finland: Nasdaq OMX Helsinki	XHEL	OMXHPI:FI	EONIA
Western	France: Euronext Paris	XPAR	CAC:FR	EONIA
Western	Germany: Frankfurt SE	XFRA	CDAX:DEF	EONIA
Western	Germany: Stuttgart SE	XSTU	CDAX:DEF	EONIA
Western	Germany: Berlin-Bremen SE	XBER	CDAX:DEF	EONIA
Western	Germany: Munich SE	XMUN	CDAX:DEF	EONIA
Western	Germany: Dusseldorf SE	XDUS	CDAX:DEF	EONIA
Western	Germany: Xetra	XETR	CDAX:DEF	EONIA
Western	Germany: Hamburg SE	XHAM	CDAX:DEF	EONIA
Western	Germany: Hannover SE	XHAN	CDAX:DEF	EONIA
Southern	Greece: Athens SE	XATH	DOM:GR	EONIA
Eastern	Hungary: Budapest SE	XBUD	BUX:HU	BUBOR
Northern	Iceland: Nasdaq OMX Iceland	XICE	OMXIPI:IC	REIBOR
Northern	Ireland: Irish SE		NQIE:IE	EONIA
Southern	Italy: Borsa Italiana	XMIL	NQIT:IT	EONIA
Northern	Latvia: Nasdaq OMX Riga	XRIS	OMXRGI:LV	EONIA
Eastern	Lithuania: Nasdaq OMX Vilnius	XLIT	OMXVGI:LT	EONIA
Southern	Malta: Malta SE	XMAL	MSETRX:MT	EONIA
Western	The Netherlands: Amsterdam SE	XAMS	AAX:NL	EONIA
Northern	Norway: Oslo SE	XOSL	OSEBX:NO	NOWA
Eastern	Poland: Warsaw SE	XWAR	WIG:PL	WIBOR
Southern	Portugal: Lisbon SE	XLIS	BVLGR:PT	EONIA
Eastern	Romania: Bucharest SE	XBSE	BET:BS	ROBID
Southern	Serbia: Belgrade SE	XBEL	BELEXLINE:RS	EONIA
Eastern	Slovakia: Bratislava SE	XBRA	SAX:SK	EONIA
Southern	Slovenia: Ljubljana SE	XLJU	SBITOP:SI	EONIA
Southern	Spain: Madrid SE	XMAD	IBEX 35	EONIA
Northern	Sweden: Nasdaq OMX Stockholm	XSTO	OMXSCAPGI:SE	STRIBOR
Northern	Sweden: AktieTorget SE / Spotlight SE	XSAT	Spotlight's index	STRIBOR
Western	Switzerland: SIX Swiss Exchange	XVTX	SPIX:CH	LIBOR
Southern	Turkey: Borsa Istanbul		XUTUM:IS	TRLIBID
Northern	Great Britain: London SE	XLON	NQGBGBP:GB	LIBOR

Source: authors' own compilation.

Appendix 2 Number of tweets posted between January 2018 and June 2020 (in thousands) in the sample