The value-relevance of social media activity of Finnish listed companies

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Abstract

Purpose – The use of social media tools by companies is common, but the links between the use of multiple social media tools by companies and stock price changes are largely unknown. Therefore, this study aims to analyze the value-relevance of social media activities on Facebook (FB), Instagram (IG), LinkedIn (LI), Twitter (TW) and YouTube (YT).

Design/methodology/approach – Stock market data and hand-picked social media data in this study were collected from Finland, a small language area with consistent International Financial Reporting Standards (IFRS) reporting practices, in the expectation of better comparability and lower noise in the data. This study uses correlation, regression and factor analyses for a sample of 105 Finnish public limited companies listed on the Nasdaq Helsinki stock exchange.

Findings – This paper finds evidence that social media activity is an important area of analysis and that the activity and popularity of a company in social media are value-relevant variables in forecasting stock prices.

Practical implications – Not all social media activities are necessarily equally important for managers and investors. Focus on visual messages in social media is recommended.

Originality/value – The findings of this study highlight the value-relevance of using multiple visual social media channels, particularly IG and YT. This paper suggests avenues for future research and for analyzing social media information.

Keywords Social media, Value-relevance, Accounting, Stock prices, Finland

Paper type Research paper

Introduction

The value-relevance of information disclosed, managed and communicated through various channels is a topic of interest in accounting and information research (Blankespoor, 2018; Isaboke and Chen, 2019; Lev, 2019). Social media are increasingly used for communicating information and social media activities resemble investments in marketing that are made to have a positive impact on a firm's reputation via the so-called electronic word of mouth (eWOM,

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see Xun and Guo, 2017). Positive sentiments related to the company may in turn influence customer behavior or loyalty (Laroche *et al.*, 2013) and affect firm performance and eventually also stock prices (Lev, 2019; Seggie *et al.*, 2007). Recently, for example, the positive sentiment in Twitter (TW) has been found as being positively related to stock returns (Duz Tan and Tas, 2021). The social media field is versatile, however, and the value-relevance of the different social media tools, when used together with other tools, is not clear, although some positive effects as a consequence of disseminating information through social media have been observed (Bartov *et al.*, 2018; Blankespoor *et al.*, 2014; Xun and Guo, 2017). In this paper, we analyze the value-relevance of multiple social media tools to ascertain whether appearances in Facebook (FB), Instagram (IG), LinkedIn (LI), TW and YouTube (YT) help explain stock price change in the Finnish context. Appearing on social media is relatively common for companies, but the impacts of the company being active (level of activity, e.g. the number of YT videos made) or popular (being liked, the number of followers or likers, etc.) in social media, especially the possible links between activity or popularity in social media tools and stock returns, are largely unknown.

Currently, legal and also voluntary information is conveyed to stakeholders largely on the internet, and many companies also engage in social media activity, such as sharing news, posts and videos and commenting on current events (Gilfoil and Jobs, 2012). However, the impacts of disclosing such voluntary information on firm value have not yet received much study. Further, there may be differences in the value-relevance of using various social media channels as well as country-specific differences in how the sentiment of social media discussions become reflected in stock prices. Our research questions are:

- *RQ1*. How is the level of social media activity linked to stock price change in the Finnish context?
- *RQ2.* How is the popularity of the company in social media linked to stock price change in the Finnish context?
- *RQ3.* How is the sentiment in social media about the company linked to stock price change in the Finnish context?

Next, we present theoretical viewpoints and discuss the possible linkages related to valuerelevance and social media. Social media activity is interpreted as how much content the organization has published. Popularity of the company is measured, e.g. by how many followers the social media profiles of the company receive. The sentiment (e.g. positive or negative) in the social media channels in general is measured by a commercial program called M-adaptive. The stock price change percentage is measured during the year 2018, which is considered to be a relatively typical year in a period when Finnish companies had already been adopting social media. In the empirical section, we study the research questions related to FB, IG, LI, TW and YT. The Finnish sample includes 105 companies from the main list of the Nasdaq Helsinki stock exchange, and control variables include the typical financial ratios portraying profitability, liquidity and financial solvency, as well as beta as a risk measure. We find that social media activity is not only a useful area of analysis but a key factor in predicting stock price changes. In particular, we find the value-relevance of IG followers, TW followers and the number of YT videos released by the company [see equation (1) and Appendix 1–6]. Further, in the discussion and conclusions section, we suggest avenues for future research.

Value-relevance and social media

Value-relevance, in a corporate context, signals that something affects the share prices of the corporation and can be used for predicting future share prices (Amir, 1993; Barth *et al.*, 2001; Lev, 2019). Barth *et al.* (2001) note that "an accounting amount is defined as value relevant if

it has a predicted association with equity market values." Traditionally, value-relevance discussions focus on accounting earnings (Isaboke and Chen, 2019) and other financial statement figures (Omran and Tahat, 2020), but currently, there is a wide range of other corporate disclosure and voluntary information available. But assessing the value-relevance of using social media is not necessarily straightforward, as there is not necessarily disclosure of social media available in the financial statements and the activities can relate to marketing, administration or information technology and only gradually affect organizational performance or stock prices (Canel and Luoma-aho, 2019; Gilfoil and Jobs, 2012; Laroche *et al.*, 2013; Lev, 2019; Luo *et al.*, 2013; Xun and Guo, 2017).

Recently, positive sentiment in TW has been found as being positively related to stock returns (Duz Tan and Tas, 2021). Further, the previous research suggests that items like reputation, brand value, social media impact or social capital may be linked to the financial value of companies (Gu and Lev, 2011; Köhler and Hoffmann, 2018; Lev, 2019; Xun and Guo, 2017). Many corporate or accounting features have been considered as potentially value-relevant, e.g. the use of IFRS, conservatism and institutional ownership (Isaboke and Chen, 2019; Omran and Tahat, 2020). For example, IFRS adoption has been seen as improving value-relevance (Isaboke and Chen, 2019), and accounting conservatism may also help to maintain the value-relevance of accounting (Kousenidis *et al.*, 2009). Yet, coverage in any mass media such as newspapers has been found to be potentially important for companies (Engelberg and Parsons, 2011; Fang and Peress, 2009). Media attention can improve accounting quality by reducing earnings management, thereby reinforcing conservative practices (Comiran *et al.*, 2018). However, media attention may also bring pressure on managers to show higher profits, thereby possibly increasing the risk of accounting manipulation (Comiran *et al.*, 2018).

The use of social media involves interaction, including possibilities to obtain vast amounts of feedback, and it has been noted that it is important to be active in social media, to respond to criticisms and to direct attention to positives, instead of not responding at all (Cade, 2018; She and Michelon, 2019). Yet, the value-relevance of multiple social media tools together or the value-relevance of the active role of a company in social media are relatively new and complex topics, and there can be difficulties in controlling the message or separating the effects of certain media or accounting practices from other practices in the context (Blankespoor, 2018; Brennan and Merkl-Davies, 2018). Further, some companies tend to be early adopters of innovations (Amir and Ziv, 1997). Typically, early adopters are those who benefit from the change or are eager to try new things (Amir and Ziv, 1997; Malmi, 1999). The early adoption of new technologies may indicate that the company is technologically in the frontline also in other current practices and can identify the trends or preferences of various stakeholder groups (Amir and Ziv, 1997; Fatmy et al., 2021; Malmi, 1999; Rautiainen and Luoma-aho, 2021; Spenner and Freeman, 2012). Adoption of social media tools involves aspects of marketing, investing and communicating so that news can be told and recruitment can be facilitated, potentially helping the future performance (e.g. operating profitability) of a company (Gilfoil and Jobs, 2012; Gu and Lev, 2011; Lev, 2019).

The impact of disclosing voluntary information on firm value has been studied regarding the social responsibility (Harun *et al.*, 2020) and earnings management of banks in Middle Eastern and North African contexts (Salem *et al.*, 2021). However, research on the valuerelevance of social media information in European context is scarce. Social media offer fast and focused ways to find target groups, the members of which typically receive added value (e.g. social and emotional value) by belonging to a certain group and commenting on products and services with others (Spenner and Freeman, 2012; Sheth *et al.*, 1991). FB visibility is not a clear measure of company image or success, however (Powell *et al.*, 2011), Valuerelevance of social media activity

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but the message needs to be conveyed to the stakeholders effectively, in a simple and readable way without giving rise to misunderstandings (Cade, 2018; Brennan and Merkl-Davies, 2018; Spenner and Freeman, 2012).

Social media activity in general has been considered value-relevant (Cade, 2018), and Luo *et al.* (2013) see social media (e.g. Web blogs) as an indicator of firm equity value. TW sentiment has been suggested as a value-relevant indicator for stock performance with a positive link between the two (Duz Tan and Tas, 2021; Gu and Kurov, 2020). This finding may be related to the notion that TW reaches a mass audience (Gu and Kurov, 2020) and reduces information asymmetry (Blankespoor *et al.*, 2014). However, the financial impacts of multiple social media tools and activities together may be indiscernible because a campaign in social media might affect other media efforts (Powell *et al.*, 2011). Companies tend to share good news more than bad news on the internet (Jung *et al.*, 2018), but the views presented in social media tools that are specifically intended for investors still seem to predict future stock returns and earnings surprises (Chen *et al.*, 2014).

The value-relevance of the different general-purpose social media tools together, particularly the popularity of the company in the tool and the activity of the company in these social media channels, has not been analyzed to our knowledge. Therefore, in this research, we analyze multiple well-known social media tools together and the value-relevance of their use, considering: the company's *activity*, such as the number of posts or videos released, the *popularity* of the company in the medium, such as the number of followers, shares and re-tweets and the general *sentiment* in the discussions in the multiple channels. The popularity indicates the use and probably also the usefulness of the medium by various stakeholders and the sentiment reveals general views about the company.

Investments in social media can be seen as building reputation, brand value and social capital, which often increase the financial value of companies (Gu and Lev, 2011; Fombrun, 2003; Köhler and Hoffmann, 2018; Lev, 2019). Understanding social media practices and their possible links to stock value may be relevant to investors and managers in decision-making. Further, social media discussions may support openness and thereby advance social and environmental issues in operations (Semenova and Hassel, 2019).

eWOM (Xun and Guo, 2017) is a term used for depicting the sentiment (or tone) of social media discussions. Xun and Guo (2017) found a positive connection between eWOM and stock prices. Further, negative comments tended to have relatively more impact than positive comments (Xun and Guo, 2017). Yet, social media sentiment studies have often focused on one tool, such as TW (Duz Tan and Tas, 2021; Gu and Kurov, 2020). Thus, the sentiment (positive/neutral/negative) in the general social media discussions (all tools/media combined) related to the company deserves analysis. As our general null hypothesis, we *assume that social media variables cannot be used to predict stock prices*. Our detailed hypotheses for the Finnish context are as follows:

- *H1.* The level of social media activity of the company is helpful for investors in predicting stock value.
- *H2*. The popularity of the company in social media is helpful for investors in predicting stock value.
- *H3.* The sentiment in social media discussion about the company is helpful for investors in predicting stock value.

Next, we present the data and methods for studying social media activity, popularity, sentiment and value-relevance.

Data and methods

The financial ratio variables were collected from the financial statements of the companies available on the internet, from the Thomson Reuters Eikon database and from Kauppalehti Web pages. The stock price change (the dependent variable in regression analyses) data is taken from the Nasdaq Helsinki stock exchange (December 31, 2017 to December 31, 2018). We focus on year 2018, when most social media tools were already relatively widely adopted in Finland but when the use of IG was not yet very widespread. The year 2018 is also considered a suitable, normal, year for study because there was variation in stock prices (some stock prices went down and some went up, after several stable high-growth years dominated by upward price movements). Further, the data is unaffected by the recent stock market fluctuations related, for example, to COVID-19.

The general social media sentiment data for each company (positive/neutral/negative) was collected during the first half of 2018 using the M-adaptive analysis tool. However, the FB, IG, LI, TW and YT variables (social media tool data, e.g. about followers and posts) were handpicked in November 2018 from the various social media channels of the companies. The timing allows initial causal considerations about predicting future stock prices, as the social media data was collected first and then the stock price change was calculated based on end-of-year (December 31, 2018) figure. However, as causality as such cannot be proved, the results are not intended for individual company investment decisions. But assuming that there is some consistency in the operations, popularity and sentiment over time, the results may give a general indication of the likely effects of social media activity for short-term investment purposes in the Finnish context. We see Finland as a suitable context, as it is a European Union country with a distinct language area and a relatively high standard of technological advancement and corporate financial reporting.

The statistical analysis was made using SPSS 26, including correlation, regression and factor analyses with both social media and typical financial variables (see Appendix 1). As control variables, we use accounting figures (Amir, 1993; Barth *et al.*, 2001; Lev, 2019), i.e. financial ratios, such as current ratio and quick ratio (depicting liquidity) and equity ratio (equity to assets, depicting solvency). Considering profitability, we analyzed return on invested capital (ROI%, i.e. net return divided by both equity capital and interest-bearing debt), return on equity (ROE%, with net return divided by equity capital), Return on assets (ROA%, i.e. net return divided by balance sheet total), operating margin (revenue less variable manufacturing costs) an operating profit (revenue less operating costs, including depreciation), as well as share-based information on price per earnings (P/E) and earnings per share (EPS). Our key dependent variable was stock price change percentage (see Appendix 1). Change or percentage figures were preferred over figures in euros because the companies were of different size. Furthermore, IFRS-based net income was used in the profitability ratios and balance sheet book values were used for company assets, equity and invested capital. Beta was used to portray company risk.

In the regression analysis, the stepwise method was used so that SPSS selected best explanatory variables from all variables (see Appendix 1). In the principal axis factoring, the most prominent factors (with eigenvalues over one) were selected for analysis. The Pearson correlations, however, were calculated between all the FB, IG, LI, TW and YT variables (social media variables from November 2018, see Appendix 1) and the company financial ratios and metrics based on the annual statements of 2017 (financial figures such as profitability; see, e.g. Lev, 2019), stock price change % (in 2018) and stock risk measures, to find evidence of the value-relevance of social media. The level of activity was judged based on the number of YT videos or posts made. Popularity of the company was judged based on the number of followers or likers and sentiment (the general tone, i.e. combined positive or

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negative views in various channels) was based on data from a commercial [1] analysis tool named as M-adaptive, which analyzes multiple social media sources for positive and negative sentiments. The social media sentiment data was collected during January 1 and June 30, 2018.

The sample size was 105 Finnish public limited companies (N = 105) listed on the Nasdaq Helsinki. The sample size is small, but the Finnish capital market is widely represented. In fact, the whole population of the main list companies was only 126 and not all companies were comparable by having enough history for the calculation of the change figures, for example. Further, not all the companies use all social media channels: typically, each social media channel had about 105 users, but only 77 used IG, i.e. they were "early adopters" of that media (Malmi, 1999). Thus, in the analyses, the *N* varies, for example, in correlation analyses after excluding missing cases pairwise, and the lowest number of useful answers in the Pearson correlation table with all variables was 58 (see Appendix 2), reflecting the smallness of the population and not a failure in sampling. Our social media data, excluding the sentiment data, were taken from the internet and the social media tools in question, i.e. from freely and publicly available sources.

Results

On average, the Finnish listed companies used 4.17 social media channels and 55.6% used all the five channels analyzed in this research. Only one company, Ovaro, a real estate company making losses at the time of this study, did not use any social media channel. Nokia clearly had the most likers or followers in social media channels. For example, on FB, Nokia had about 13 million followers, whereas Fiskars had about 870, 000 and the third biggest company, Finnair, had about 620, 000 followers. When leaving Nokia out of the analysis as an outlier, we find that on average Finnish listed companies got about 46, 000 followers. In the group of medium-size companies according to Nasdaq Helsinki categorization, Rapala, F-secure and Rovio were the most popular with over 225, 000 followers. From the small companies, only Marimekko had over 100, 000 followers. From the M-adaptive data we found that Elisa, a mobile phone operator, had the most positive sentiment, about 48% of the discussions. The biggest negative sentiments, still below 12% of all discussions, were received by Tieto, F-Secure and Rovio.

In the Pearson correlation analysis, we found that the number of FB likers did not correlate with stock price change %. Instead, the number of IG followers had a positive significant correlation with price change, even if the number of FB likers and IG followers correlated positively (Appendix 2). Further, the sentiment (positive or negative) of general social media discussion did not correlate with stock price change (see Appendix 2).

In the regression model where the dependent variable was *stock price change* % (Δ P-%), it was found that not only is social media activity a useful area of analysis but a key issue in assessing current stock market behavior. Many of the social media variables (e.g. TW followers and IG followers) correlated positively as variables. However, in the following final model (with stepwise linear regression in SPSS, see Appendix 3) it is noteworthy that the coefficients of the variables IG followers and TW followers had opposite signs and further that FB or LI did not appear in the final model at all. This may suggest some multicollinearity, although that was not a big problem in the final model (with the biggest variance inflation factor, VIF, being 3.48, see Appendix 3). However, this also suggests that the combined use of multiple social media tools can be complex and that all social media activity is not equally important for investors, for example if LI is used more for recruitment. Further, even though the coefficient for the number of YT videos was positive (see Appendix 3), it was very small, virtually zero, so it has been marked as "0.0a" in the

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following final model where the other independent variables are IG followers and TW followers. So equation (1) is:

Price change
$$\% = -0.310 + 3.2 E - 6 * IG$$
 followers $-6.6E - 6 * TW$ followers $+0.0a * YT$ no. of videos

The R^2 for this model was 0.387, i.e. about 39% (see Appendix 3). This suggests that in the Finnish context, a million new IG followers would imply a 3.2% rise in the stock in a year (see Appendix 3) [2]. The negative coefficient related to TW may indicate that there may be differences among the views of the users of different social media channels.

This result indicates that all social media channels are not necessarily equally important. YT seems an important channel in social media marketing and stakeholder work, even though the value of a single added video may typically be small. In our view, the results suggest the value-relevance of visual messages, such as pictures (particularly in IG) and videos (in YT) because both these received positive coefficients in the regression model. This relates to the interesting finding that TW followers get negative coefficients in the models. So there seem to be differences in the value-relevance of various social media tools when used together with other social media tools. The results support the H1 [e.g. the number of videos made in equation (1)] and the H2 [e.g. visible in the number of IG followers in equation (1)]. So in our sample, in particular, the popularity of the company in IG and activity of the company in YT are positively linked to stock value, indicating that they are value-relevant and can be used in predicting stock value. The popularity of the company in social media tools (number of likers or followers, etc.) was not directly linked to organizational performance, however, if measured with operating profitability (see Appendix 2).

Our result that no financial ratio appears in the final regression model [equation (1) created using the stepwise analysis in SPSS] is partly surprising. The typical control variables such as financial ratios, company size and industry or field dummy were tried, but none of them were statistically significant; hence, using other variables did not improve the final model but resulted in a lower R^2 value. Our industry dummies included two fields: consumer products and industrial products, which were considered relevant in the social media setting, where consumer products and services are expected to receive more public attention than industrial Business-to-Business products and services. Further, the company size was categorized into three groups: small, medium and large cap. However, considering also the positive correlation between IG followers and stock returns (0.398, p < 0.01), our findings corroborate the idea that social media is value-relevant (Luo *et al.*, 2013, although they did not consider individual tools like IG or TW) by finding that popularity of the company at least in some social media channels is useful in predicting future stock performance.

A factor analysis was conducted regarding the social media and financial statement variables to test if the social media tools represent the same underlying latent variable. However, factors labeled as *popularity*, *participation*, *profitability*, *liquidity and viral* were found, so that there are different emphases or phenomena (multiple factors) related to social media variables (and in the financial ratios related to profitability and liquidity). Popularity factor had most explanatory power, i.e. it generally explained variances in all the variables, indicating possibly some value-relevance of generally popular messages in the social media (the correlation is, however, not significant, with *p*

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(1)

= 0.057, as shown in Appendix 5) but at least that the numbers of followers or likers in various channels tend to correlate positively. The *viral* factor included creating IG publications that are widely and positively approved (according to the three biggest loadings for the viral factor, shown in Appendix 4), and in a stepwise regression analysis conducted with the factors, it was the only significant factor in explaining the stock price change (with an R^2 of 11.5%, Appendix 5). In our Finnish context, this suggests that for acquiring a competitive advantage, popularity alone is not the key but the message benefits from being interesting and positively approved, particularly in IG in our case. Our sample size was small considering factor analysis; nevertheless, these findings indicate that viral messages are important and that all social media tools do not necessarily represent the exact same phenomenon. This supports the point that there are benefits in the early adoption of methods or tools (Amir and Ziv, 1997) and being active in creating image and communicating with stakeholders.

Finally, the stepwise regression model in equation (1) was reexamined together with typical accounting variables or ratios representing for example profitability analysis (in terms of RoE, see, e.g. Lev, 2019) to find additional information on the possible effects of financial and social media variables. However, the social media variables still were the most important explanatory variables for stock price change (Appendix 6). Further, considering the value-relevance of sentiment in general social media discussions and *H3*, we did not find any evidence through correlation (see Appendix 2) or regression analyses and so here *H3* is rejected and the null hypothesis remains.

Discussion and conclusions

We found that the social media activities of companies were linked to stock value change. Activity in the use of social media and especially the popularity of IG in our sample indicate positive stock price changes. We suggest that activity in social media needs to be focused, preferably with visual and to-the-point messages that are easily shareable. The linear regression model [equation (1)] explaining stock price change with IG followers, TW followers and the number of YT videos released by the company yielded an R^2 value of about 39%. Thus, a general null hypothesis that social media variables have no valuerelevance, or cannot be used in predicting stock returns, is rejected. Instead, H1 can be accepted. Considering H2, we find positive evidence but, importantly in our sample, IG and TW seemed to be more important than other social media tools. However, regarding H3. there was no corroborating evidence regarding either positive or negative sentiments. We therefore argue that visual social media channels are particularly important and valuerelevant indicators of positive stock price changes and so require managerial attention. To the best of our knowledge, we believe this visual emphasis to be our first contribution and an elaboration on the earlier views on the value-relevance of social media and more generally of communication in the corporate world (Canel and Luoma-aho, 2019; Gu and Lev, 2011; Lev, 2019; Luo et al., 2013).

TW, especially with a positive sentiment, has been seen as a value-relevant tool (Bartov *et al.*, 2018; Duz Tan and Tas, 2021; Gu and Kurov, 2020) that reduces information asymmetry (Blankespoor *et al.*, 2014). In this research, however, we analyzed the different social media tools together and found that overall sentiment in social media was not very important in the Finnish context and that actually the number of TW followers received a negative coefficient in equation (1). This may suggest that TW users have more critical attitudes than other social media users or that positive hubris can be easier to create with visuality [3]. However, this provides our second contribution in understanding the value-relevance of the combined use of social media tools and their differences and connections

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(through regression and factor analysis), where we showed different emphases in the valuerelevance of various social media tools. We further showed that social media sentiment is not a clear indicator of value when used in combination with other tools (widening the view about social media tools and eWOM presented in Bartov *et al.*, 2018; Gu and Kurov, 2020; Xun and Guo, 2017). However, further research on sentiment and the role of various tools (both activity and popularity), particularly TW, LI and FB, is required before drawing strict conclusions about the value-relevance of the tools in combined use with other social media in various contexts. Yet, we can agree with Spenner and Freeman (2012) and with Brennan and Merkl-Davies (2018) that those companies that can identify the preferences of their key stakeholders and communicate information effectively may use their (social) media mix better to support their business and information management, which suggests improved value in the long term.

In this paper, the sample size was relatively small (105 companies) because of the small Finnish market area, but on the other hand, we see Finland as a clearly distinguishable language area for sentiment analyses. The sentiment, either positive or negative, was not significant in the regression analysis in explaining stock price changes. However, our factor analysis showed that the viral factor was positively and significantly related to the stock price change percentage, suggesting that, in addition to popularity, the company benefits from interesting and positively approved visual messages.

Thus, not only the social media tools that are specifically intended for investors (Chen *et al.*, 2014) but several social media tools are value-relevant and information related to social media can facilitate the prediction of future stock prices. Further, the combined use of visual social media tools is recommended: for example, YT seems to be an important channel and it is able to explain stock performance in our data together with IG and TW (thus widening the earlier results related to TW only by Xun and Guo, 2017). Our results did not highlight the value-relevance of sentiment, however, although the different social media variables typically correlated positively. Further, the value-relevance of IG suggests that companies with good news may be more prone to adopt new tools and that the early adoption of social media tools, too, may be a sign of understanding trends and reputational issues, often gradually indicating also transparency and good stock market performance (Amir and Ziv, 1997; Fatmy *et al.*, 2021; Malmi, 1999; Spenner and Freeman, 2012).

Considering the managerial implications, managing voluntary information disclosure and information (e.g. visual messages) also in social media channels seems important. The visual issues in information management, e.g. on YT and IG, seem to be important, suggesting that the visual image and short, precise presentation of the company communication can be used to create value. Social media can be of significance also for investors, because there is a continuous feed of real-time information to complement the quarterly financial reports, possibly allowing opportunities for short-term investing as well as active ownership roles even for private investors (Semenova and Hassel, 2019). Yet, there are different types of companies and different markets, where popularity or the level of activity may be difficult to compare (see Appendix 7 for a note on comparable social media analysis (SMA) among markets, the SMA index).

Despite the relatively small amount of data, this research showed findings that serve as a comparison for further research when analyzing the current COVID-19-era capital markets. This study opens up several avenues for future research: bigger samples for measuring social media activity are recommended and also analyses of different Valuerelevance of social media activity

IJAIM 30,2 combinations of social media tools. Further, incorporating social media variables into more traditional studies, for example concerning earnings management (Salem *et al.*, 2021) or value-relevance of information in different types of firms (e.g. with high institutional ownership, see Omran and Tahat, 2020), could be useful for both scholars and practitioners in their analyses, revealing new value-relevant aspects of current business contexts. Studying the value-relevance of social media tools over a longer term (considering the possible time lag in effects) might also deserve more attention. Further, these research avenues might reveal underlying variables that affect both stock price changes and social media activity simultaneously and therefore offer insights into social media tools seem more value-relevant than others. Finally, the current COVID-19 pandemic may have accentuated the meaning and relevance of social media and the internet generally; therefore, this area deserves further analysis.

Notes

- 1. If a commercial sentiment analysis tool is not available, based on the results of this study, the sentiment analysis might be left out of the analyses. We consider such smaller-scale social media analysis (SMA) and company comparisons also in terms of a novel SMA index in Appendix 7.
- 2. For additional information, a standardized formula is presented. When the independent variables have a different unit of measure, it may help the interpretation of the original equation to know what kind of changes we expect in the dependent variable if any independent variable in the equation changes by one standard deviation. Further, in a standardized formula, there is no constant term. For example, the numbers of followers tend to be bigger than the number of posted videos and so we might get a more comparable view of the relative effects of the independent variables with the following standardized equation, equation (2): *Price change* % = 0.926*IG followers 0.622*TW followers + 0.329*YT No. of videos. This further highlights the role of IG followers in our analysis.
- 3. We thank one of the anonymous reviewers of this paper for pointing out possible interpretations for the negative TW coefficient sign.

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Appendix 1. Social media, stock market and financial statement analysis variables

Social media variables

- Facebook: likers
- Twitter: followers
- Twitter: tweets
- Instagram: followers
- Instagram: publications
- LinkedIn: followers
- · LinkedIn: updates
- YouTube: subscribers
- YouTube: views

- YouTube: number of videos
- Social media amount (number of company-related mentions, posts, etc. from the M-adaptive program)

Sentiment (from the M-adaptive program)

- Positive sentiment proportion (%)
- Neutral sentiment proportion (%)
- Negative sentiment proportion (%)

Company and stock exchange variables

- Consumer products industry field dummy
- Industrial products industry field dummy
- Company size 1–3 (1 = small, 2 = medium and 3 = large, according to Nasdaq Helsinki categories)
- Beta
- P/E
- Price change % 2018 (the dependent variable)

Financial ratios

- Current ratio
- Quick ratio
- EPS
- Operating margin (%)
- Operating profit (%)
- Net profit (%)
- ROI (%)
- ROE (%)
- ROA (%)
- Equity ratio (%)

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Appendix 2. Pearson correlations for key variables

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3	1	4
0	-	

30,2	Neutral	-0.043 0.665 105	0.014 0.885 105	-0.201 * 0.039 0.039	-0.108 0.308 91	-0.104 0.317 94	-0.159 0.126 94	-0.157 0.111 105	32 -0.132 35 0.183 104 24 -0.112 77 0.365 68 (continued)
314	Negative	-0.104 0.292 105	-0.021 0.834 105	$\begin{array}{c} 0.052 \\ 0.595 \\ 105 \end{array}$	0.094 0.377 91	0.098 0.346 94	0.267** 0.009 94	0.129 0.189 105	0.062 0.535 104 -0.004 0.977 68 (<i>com</i>
	Positive	0.105 0.289 105	-0.038 0.701 105	$\begin{array}{c} 0.205 \\ 0.036 \\ 105 \end{array}$	0.090 0.398 91	0.083 0.427 94	0.113 0.279 94	0.144 0.144 105	0.159 0.107 104 0.143 0.143 0.244 68
	Social media amount	-0.054 0.583 105	-0.216* 0.027 105	0.027 0.786 105	0.080 0.453 91	0.078 0.454 94	0.147 0.157 94	0.146 0.137 105	0.351*** 0.000 104 0.060 0,638 68
	YT no. of videos	0.240* 0.021 92	0.125 0.234 92	-0.010 0.923 92	0.185 0.091 85	0.178 0.094 90	0.351^{**} 0.001 90	0.215* 0.040 92	0.315** 0.002 92 0.124 0.332 63
	YT views	0.102 0.337 91	$\begin{array}{c} 0.179 \\ 0.089 \\ 0.1\end{array}$	0.040 0.708 91	0.153 0.162 85	0.129 0.228 89	0.286** 0.007 89	$\begin{array}{c} 0.111\\ 0.295\\ 91 \end{array}$	0.136 0.198 91 0.212 0.095 63
	YT subscrib-ers	0.185 0.084 88	0.051 0.635 88	-0.007 0.951 88	0.992*** 0.000 83	0.996*** 0.000 86	0.600** 0.000 86	0.940*** 0.000 88	0.341** 0.001 88 0.840** 0.000 61
	IG publicat-ions	0.206 0.092 68	0.134 0.277 68	0.004 0.975 68	0.040 0.749 66	0.030 0.813 64	-0.035 0.782 64	0.037 0.765 68	-0.012 0.924 68 0.298* 0.013 68
	IG followers	0.398*** 0.001 68	0.100 0.416 68	0.081 0.511 68	0.849*** 0.000 66	0.841*** 0.000 64	0.396*** 0.001 64	0.790*** 0.000 68	0.240* 0.048 68 1 68
	LI updates	0.226* 0.021 104	-0.106 0.286 104	-0.068 0.493 104	0.298** 0.004 90	0.317^{**} 0.002 94	0.399^{**} 0.000 94	0.436^{**} 0.000 104	104
	LI followers	0.169 0.084 105	-0.012 0.903 105	$\begin{array}{c} 0.080 \\ 0.415 \\ 105 \end{array}$	0.939^{**} 0.000 91	0.945** 0.000 94	0.476** 0.000 94	$^{1}_{105}$	
	TW tweets	0.059 0.570 94	-0.086 0.408 94	-0.095 0.363 94	0.475** 0.000 85	0.493** 0.000 94	1 94		
	TW followers	0.144 0.166 94	0.050 0.635 94	0.006 0.958 94	0.996*** 0.000 85	1 94			
	FB likers	0.156 0.140 91	-0.005 0.966 91	0.016 0.877 91	1 91				
	ROI%	0.124 0.206 105	-0.158 0.108 105	1 105					
	Oper. profit %	-0.158 0.108 105	$1 \\ 105$						
	Price change	0							
Table A1. Pearson correlations	Variable	<i>Price change</i> Correlation Sig. (two-tailed) <i>N</i>	<i>Oper. profit %</i> Correlation Sig. (two-tailed) <i>N</i>	ROI% Correlation Sig. (two-tailed) N	FB likers Correlation Sig. (two-tailed) N	<i>TW followers</i> Correlation Sig. (two-tailed) <i>N</i>	<i>TW tweets</i> Correlation Sig. (two-tailed) <i>N</i>	LIfollowers Correlation Sig. (two-tailed) N	LI updates Correlation Sig. (two-tailed) N IG followers Correlation Sig. (two-tailed) N

Variable cl	Price change	Oper. profit %	ROI%	FB likers	TW followers	TW tweets	followers	LI updates	IG followers		IG YT publicat-ions subscrib-ers	YT views	YT no. of videos	Social media amount	Positive	Positive Negative	Neutral
IG Publications Correlation Sig. (two-tailed) N										1 68	0.047 0.720 61	0.217 0.087 63	0.110 0.393 63	0.057 0.643 68	0.313^{**} 0.009 68	-0.042 0.733 68	-0.225 0.065 68
YT Subscribers Correlation Sig. (two-tailed) N											88 1	0.182 0.089 88	0.217* 0.042 88	0.080 0.460 88	0.086 0.427 88	0.082 0.448 88	-0.102 0.344 88
YT Vieus Correlation Sig. (two-tailed) N												1 91	0.533^{**} 0.000 91	0.212* 0.044 91	0.294^{**} 0.005 91	0.010 0.924 91	-0.256* 0.014 91
YT no. of videos Correlation Sig. (two-tailed) N													1 92	0.237* 0.023 92	$\begin{array}{c} 0.271^{**} \\ 0.009 \end{array}$	0.234* 0.025 92	-0.298*** 0.004 92
Social media amount Correlation Sig. (two-tailed) N	<i>tt</i>													$1 \\ 105$	0.462^{**} 0.000 105	$\begin{array}{c} 0.254^{**} \\ 0.009 \\ 105 \end{array}$	-0.456^{***} 0.000 105
Positive Correlation Sig. (two-tailed) N															$1 \\ 105$	$\begin{array}{c} 0.384^{***} \\ 0.000 \\ 105 \end{array}$	-0.956^{***} 0.000 105
Negative Correlation Sig. (two-tailed) N																$1 \\ 105$	-0.613^{***} 0.000 105
Neutral Correlation Sig. (two-tailed) N																	1 105
Notes: *Correlation is significant at the 0.05 level (two-tailed). **Correlation is significant at the 0.01 level (two-tailed)	n is signi	ficant at the	e 0.05 level	l (two-taile	3d). ***Correlat	tion is sign	ificant at the	0.01 level (tv	vo-tailed)								

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Table A1.

		Ct.J 200000 24		Change	Change statistics		C:~ 12	
		start of the estimate	R^2 change	F change	df1	df2	olg. r change	Durbin-Watson
0	0	0.279954704000	0.193	12.937	Ч	54	0.001	
0	0.	0.266675218000	0.088	6.512		53	0.014	
0	0.	0.248732263000	0.105	8.922	-1	52	0.004	1.855

Appendix 3. Stock price change regression [equation (1)]

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Table A2.Model summary^d

	Unstand		Std. coefficients			Collinea statisti		relevance of social media
Model	В	Std. error	Beta	t	Sig.	Tolerance	VIF	activity
l (Constant)	-0.233	0.039		-6.033	0.000			
IG followers	1.535E-6	0.000	0.440	3.597	0.001	1.000	1.000	317
2 (Constant)	-0.240	0.037		-6.521	0.000			011
IG followers	3.153E-6	0.000	0.903	4.186	0.000	0.291	3.431	
TW followers	-5.818E-7	0.000	-0.550	-2.552	0.014	0.291	3.431	
3 (Constant)	-0.310	0.042		-7.461	0.000			
IG followers	3.233E-6	0.000	0.926	4.598	0.000	0.291	3.436	
TW followers	-6.577E-7	0.000	-0.622	-3.071	0.003	0.287	3.480	
YT no. of videos	0.000	0.000	0.329	2.987	0.004	0.973	1.028	
								Table A3.
Notes: ^a Dependent va	riable: price c	hange % 201	8 VIF = Variance i	nflation fa	rtor			Coefficients ^a

Appendix 4. Factor analysis

IJAIM 30,2

	Variables	1 Popularity	2 Profitab	Factors 3 Liquidity	4 Participation	5 Viral
318	TW followers	0.990				
	FB likers	0.983				
	LI followers	0.955				-0.131
	IG followers	0.897				0.323
	No. of observations	0.894				0.231
	TW tweets	0.625			0.377	-0.199
	Beta 31.12.2017	0.370	-0.187		-0.127	
	ROE%		0.999		-0.186	-0.101
	ROI%		0.983		-0.246	-0.133
	Operating profit %		0.844	-0.148	0.141	
	EPS€	-0.138	0.699		0.227	
	Operating margin %		0.693		0.193	0.102
	P/E		0.310			
	Current ratio 2017			0.981		
	Quick ratio 2017			0.937		-0.121
	Equity to balance sheet total %		0.117	0.770		
	YT no. of videos				0.818	
	YT views		0.118	0.110	0.573	0.192
	LI updates	0.316		-0.153	0.343	-0.267
	Negative				0.147	
	IG publications		-0.119	-0.117		0.654
	Positive		0.268	-0.113	0.232	0.395
Table A4.	Notes: Extraction method: prin		ing. Rotation r	nethod: Proma	x with Kaiser norm	nalization

Pattern matrix^a

^aRotation converged in six iterations

	Factor	1	2	3	4	5
	1	1.000	0.051	-0.055	0.283	0.045
	2	0.051	1.000	-0.183	0.216	0.223
	3	-0.055	-0.183	1.000	-0.075	-0.110
(T) 1 1 A =	4	0.283	0.216	-0.075	1.000	0.084
Table A5.Factor correlation	5	0.045	0.223	-0.110	0.084	1.000
matrix	Notes: Extr	action method: princi	ipal axis factoring. R	Rotation method: Prop	max with Kaiser nor	malization

	x 5. Pears	son corre	lations fo	or factors	and regro	essions			Value
Price change % 2018	0.251 0.057 58	0.073 0.587 58	0.147 0.271 58	0.258 0.050 58	0.339*** 0.009 58	-0.068 0.499 102	0.193* 0.049 105	1 105	relevance o social medi activit
Net profit %	0.102 0.446 58	0.909** 0.000 58	-0.335* 0.010 58	0.345*** 0.008 58	0.240 0.069 58	$\begin{array}{c} 0.053\\ 0.594\\ 102\end{array}$	1 105		31
Beta 31.12. 2017	0.324* 0.013 58	-0.207 0.119 58	0.007 0.958 58	-0.071 0.595 58	-0.107 0.423 58	$1 \\ 102$			
REGR factor 5 viral	0.046 0.732 58	0.224 0.092 58	-0.126 0.346 58	0.086 0.522 58	1				Q
REGR factor 4 particip.	0.299* 0.023 58	0.239 0.071 58	-0.074 0.579 58						it the 0.01 level (two-tail
REGR factor 3 liquid.	-0.054 0.689 58	-0.186 0.163 58	1 58						rrelation is significant a
REGR factor 2 profitab.	0.051 0.703 58	1							5 level (two-tailed). **Co
REGR factor 1 popularity	1 (popularity) 1 58	2 (profitability)	3 (liquidity)	4 (participation)	5 (viral)			18	Notes: *Correlation is significant at the 0.05 level (two-tailed). **Correlation is significant at the 0.01 level (two-tailed) and some related correlation is significant at the output of the output
Variables	REGR factor score 1 (popularity) Correlation Sig. (two-tailed) N	REGR factor score 2 (profitability) Correlation Sig. (two-tailed) N	REGR factor score 3 (liquidity) Correlation Sig. (two-tailed) N	REGR factor score 4 (participation) Correlation Sig. (two-tailed) N	REGR factor score 5 (viral) Correlation Sig. (two-tailed) N	Beta 31.12.2017 Correlation Sig. (two-tailed) N	<i>Net profit</i> % Correlation Sig. (two-tailed) <i>N</i>	Price change % 2018 Correlation Sig. (two-tailed) N	Table Ad Stock price chang * and some relate correlation

IJAIM 30,2		Durhin_	Watson	1.943			
320		Sig F	change	0.009			
			df2	56			
		Change statistics	df1	1			
	5	Change	F change	7.273	ange % 2018		
	Model summary ^b		R^2 change	0.115	variable: price ch		
	Mode	Std error of	the estimate	0.2960332	Notes: ^a Predictors: (constant), REGR factor score 5 for analysis 2 ^b Dependent variable: price change % 2018		
		Adinstad	R^2	660.0	actor score 5 for a		
			R^2	0.115	stant), REGR fa		
Table A7. Regression analysis for price change and			R	0.339^{a}	redictors: (con:		
factors (only one factor found significant)			Model	1	Notes: ^a P ₁		

Va	1.000	VIF
relevan social m act	1	Collinearity stats. ince
act	1.000	Collin sta Tolerance
	1.	Tole
	0.000	Sig.
	-5.096 2.697	t
	0.339	Std. coefficients Beta
	0.039 0.044	Unstandardized coefficients Std. error
	-0.198 0.119 $6\ 2018$	Unstan coeff <i>B</i>
	1 (Constant) –0. REGR factor score 5 (viral) 0. Note: ^a Dependent Variable: price change % 2018	
Tabl Coeffi	ote: ^a I	Model

IJAIM 30,2 Appendix 6. Regression with accounting variables Std. error of Change statistics 322 \mathbb{R}^2 change \mathbb{R}^2 Adjusted \mathbb{R}^2 Model R the estimate F change df2 df1 Sig. F change 1 0.636^{a} 0.405 0.257506 4.247 8 50 0.309 0.405 0.001Table A9. **Notes:** ^aPredictors: (constant), negative, IG followers, equity to balance sheet total %, ROE%, YT no. of videos, beta 31.12.2017, current ratio 2017, TW followers. ^bDependent variable: price change 2017–2018 Model summary^b

Model		lardized cients Std. Error	Standardized coefficients Beta	t	Sig.	Collinea statisti Tolerance	2	Value- relevance of social media
1 (Constant)	-0.428	0.178		-2.400	0.020			activity
ROE%	-0.078	0.295	-0.030	-0.263	0.794	0.903	1.107	
Equity to balance sheet total %	0.509	0.359	0.236	1.419	0.162	0.432	2.313	000
Current ratio 2017	-0.016	0.040	-0.067	-0.402	0.690	0.433	2.312	323
Beta 31.12.2017	-0.053	0.096	-0.069	-0.556	0.581	0.779	1.284 •	
IG followers	2.869E-6	0.000	0.798	3.838	0.000	0.275	3.632	
TW followers	-4.994E-7	0.000	-0.459	-2.102	0.041	0.250	4.001	
YT no. of videos	0.000	0.000	0.303	2.637	0.011	0.901	1.109	
negative	-1.586	1.370	-0.131	-1.158	0.252	0.926	1.080	
Notes: ^a Dependent variable: price	change 2017	–2018. Regi	ession method:	Enter				Table A10. Coefficients ^a

Appendix 7. The SMA index

A possible way for private investors with limited resources for analyzing social media without commercial internet analysis programs, such as M-adaptive, could relate, based on our results, not so much on the sentiment in general but on popularity (followers) and the level of activity (judged e.g. by the number of YouTube videos). Yet, companies may be of different sizes and from different market areas. Therefore, social media activity (SMA) index is presented as a tool for comparing companies from different markets, including two components: *popularity* and *level of activity*. These two components are given a scale, e.g. points 1–100, a percentage scale as compared with a benchmark company in the market (or field or country). Adding up the component points would then give the total SMA index points, where the maximum is 200 points, and this number might then be used as a potential variable in further value-relevance analyses to support investment decisions or analyses related to different markets.

The *popularity* component is relatively easy to measure; for example, the number of those liking (number of "likes") or following (number of followers) the company or its messages. Comparing an individual company to a benchmark, such as the figures of the market leader (or to the highest numbers in the field) offers a way to increase comparability. *Level of activity* refers to whether the company has invested in continuous visibility in social media: e.g. actively publishes new material, such as posts or videos. Again, the activity level grades might be scaled against a suitable benchmark company in the market in question.

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