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STRUCTURAL BREAKS, TWITTER, AND THE STOCK LIQUIDITY OF INTERNET DOT-COM COMPANY: EVIDENCE FROM US COMPANIES

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Abstract:

The goal of this paper is to explore relationship between Twitter and stock liquidity of some large US internet Dot-com companies in the presence of unknown structural breaks for the period from September 2019 to April 2020. Using the Andrews-Ploberger and Andrews-Quandt structural break models, we identify the major structural breakpoints in the stock liquidity and find that most of these structural changes are significantly perceived. When we examined the sub periods as well as the full sample, Tweets and likes from most numbers of companies were found not to have links with stock liquidity. These results provide crucial insight into portfolio strategy to both international and local investors.

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INTRODUCTION

Dot-com companies are companies that do their businesses strictly on the internet with a known website on the World Wide Web (WWW) with the domain ".com". The ".com" domain of a website URL usually (but not always) indicates commercial or profit oriented companies (compared to the companies with ".org" domains which are usually used for commercial or non-prof organization), see Wikipedia[1]. The ".com" companies conduct their businesses, be those products or services, via web-based mechanism, even when tangible goods, products, or services are involved. However, some ".com" companies do not deal with tangible products. Many of these companies respond or communicate with customers and investors through their social media handles, particularly Twitter. Scientific research has shown the existence of a relationship between Twitter's tweets, "likes", retweets, etc., and stock market activities, (see Pöppe *et al.*, 2020, Guijarro *et al.*, 2019, Shiva and Singh, 2019, Broadstock and Zhang, 2019). Structural change is common in stock prices relationships, and it can be quite risky to ignore.

1 Wikipedia, Dot-com company https://en.wikipedia.org/wiki/Dot-com_company

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This can cause inferences to go astray, inaccurate forecasts, and misleading policy recommendations. Therefore, the goal of this paper is to explore the role of Twitter and stock liquidity of US internet Dot-com companies in the presence of unknown structural breaks.

In past decades, investors got information about market situation through watching television, reading newspapers, or by word-of-mouth from friends and families. But with the advent of social media, the ways how information is generated and dispersed on financial markets have fundamentally been transformed (Dugast & Foucault, 2016). Unarguably, social media have significantly influenced daily human lives and changed the way individuals and businesses perform, create awareness, and seek advice (Nisar & Yeung, 2018). For the past decade, Twitter has remained one of the largest social media microblogging service providers that has shown steady growth both in its services and the number of subscribers. Twitter networking service allows users (subscribers) to post and interact with messages referred to as "tweets." Launched in 2006, Twitter currently has 330 million active subscribers and 145 million daily active users (Twitter, 2020). Twitter has grown in popularity and reliability as a means of messaging for individuals, and an official channel of communication by many corporate organizations. Tweets from Twitter usually contain short text messages within 140 characters. Just like individuals, companies also maintain Twitter accounts, so as to create a two-way communication channel where customers can publicly communicate with companies and leave the record public. With abundance of information available online, scholars and practitioners have successfully applied Twitter data to predict and analyze several variables ranging from health, politics, academics, biology, financial markets, and stock markets, etc. Twitter has widespread coverage and is generally accepted both in the financial sector and research community.

However, avalanche of studies exists on the relationship between Twitter and financial markets. And some studies (such as those conducted by Saurabh and Dey (2020), Albarrak *et al.* (2020), Affuso and Lahtinen (2019), Ge *et al.* (2019), Behrendt and Schmidt, A. (2018), Zhang *et al.* (2018), etc.) have revealed the existence of a link between Twitter and stock market. Also, numerous studies and events have clearly shown that Twitter influences both the companies and the market. For example, on the 23rd of April 2013, the Associated Press Twitter account was hacked, and the hackers posted "Breaking: Two Explosions in the White House and Barack Obama is injured". This incident caused a 0.9 percent immediate decline in the S&P 500. Empirical studies have revealed that Tweets and sentiments associated with Twitter have shown to impact return on investments. If so, does it also affect stock liquidity? Also, given that under the same economic conditions, stock liquidity of separate companies is different, the question is: Does company capitalization affect the relationship between Twitter and stock liquidity? We provide an empirical analysis of the role of social media, specifically Twitter and stock liquidity by tracking the history of individual companies tweets and the corresponding likes.

Liquidity is a complex concept and one of the most researched area in theory of finance simply because of its role in functioning of the financial markets. Hence, O'Hara (2004) said "liquidity is hard to define, but easy to feel it". Generally speaking, liquidity refers to the ease with which assets are sold immediately after purchase without incurring any forms of losses. These losses could be results of price changes or various transaction costs. Therefore, whenever investors consider investing an asset, some of the first things to thoroughly consider are: the ability to re-sell it, its future cost, as well as the price to sell at. These various forethoughts relate to asset liquidity and these issues which are to be considered can potentially affect the cash flow of the asset. Future cash flows are known to affect liquidity; hence it is seen as an important factor in asset pricing. However, forced sales with regards to price reduction and cost trading are not pricing factors that are significantly related to a financial asset like stock. Therefore, higher measure of non-liquidity attracts the risk of higher losses for the investors along with higher gains in comparison to the liquid markets due to price volatility.

On liquidity market, investors remain uncertain when it comes to performing large transaction as it may create significant price change which can cause higher losses. Therefore, stock market development is impeded as higher illiquidity lowers down capital inflows.

Apart from financial stock market liquidity which this study focuses on, the concept of liquidity can also be explained in other forms: (i) asset liquidity; (ii) an asset market liquidity; (iii) a financial market liquidity and (iv) the liquidity of a financial institution. Understanding the microstructure of the market is important. Hence, number of studies have proposed liquidity measures as proxies for investors' liquidity and transaction costs. Datar *et al.* (1998) proposed liquidity tests based on turnover rate. Specifically, whilst the former uses the turnover rate as a proxy for liquidity that correlate with trading frequency, the latter employs the turnover rate in a cross-sectional regression to perform an experiment. Their study reveals stock returns as a decreasing function of the turnover rates. Amihud (2002) introduced the illiquidity index to measure liquidity with regard to the traded volume. The illiquidity measure is the average of the daily impacts over a particular sample period, thus provides an understanding of the relations between volume and price change.

Apart from the volume-type liquidity indices already enumerated, another group of liquidity measure is the price-type liquidity index. This category includes measures that use asset or market liquidity based on price behavior (Gabrielsen *et al.,* 2011). The Market Efficient Coefficient (MEC) is another liquidity measure that assesses the effects of execution costs on price volatility over short period of time. This measure is also known as the variance ration which is a widely used liquidity index in many empirical references. The notion is that more liquid market indicates smaller variance of transaction around equilibrium price. The bid-ask spread, and its variants have also been relied on and used by economists and other market participants as liquidity measure. This is because, it conveys insightful information about market conditions. The bid-ask spread can also be explained as the difference between the lowest ask price and the highest bid price. However, in this study, we apply the Amihud (2002) illiquidity ratio to determine the stock liquidity for the US internet Dot-com companies. It is the most commonly used and generally accepted liquidity proxy by scientists, academia, economists, stocks participants, etc.

Nevertheless, numerous studies have examined the relationship between Twitter and stock market activities (Sakhare *et al*., 2020; Fan *et al*., 2020; Broadstock & Zhang, 2019; Chahine & Malhotra, 2018). While most of these studies found meaningful relationship, other literature documents offered contrary results. Similarly, it is of common knowledge that economic shocks, global pandemic, political incidents and unrests, policy alterations, etc., greatly affect companies' revenue. According to Amihud (2002) conventional liquidity ratio, etc., are known market liquidity indices which depend on the traded stock volume and change in prices. And if this is so, do companies' tweets and "likes" influence liquidity in the presence of structural changes? Again, are these structural breaks in companies' liquidity connected to or relevant for the global pandemic crisis of COVID-19 even as the companies continue to tweet? First, we attempt to identify the structural break points in the time series of companies' liquidity with external Twitter variables, using Andrews-Ploberger (1994) and Andrews-Quandt Structural Break Tests which allow for the presence of breaks in a linear model.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature related to structural break, Twitter, and stock liquidity. Section 3 discusses the data as well as methodology applied in our empirical analysis. Section 4 reports and discusses the results of our empirical analysis, whereas the section 5 is the summary of our research study.

LITERATURE

Factors which can cause structural changes in countries, markets, and industries include new economic development, global shifts in labor and capital, changes due to disaster, changes as a result of global pandemic, changes due to demand and supply of resources. That is why academia, policy makers, and other concerned stakeholders conduct ex ante or ex post research to investigate theses structural changes in numerous financial and economic variables. Ruch *et al.* (2020), Anguyo *et al.* (2020), Hegerty (2020), Nath and Sarkar (2019), Gil-Alana (2019), Orlowski (2017) examine the break dates and the impact of structural changes on inflation series with regards to other variables. Ruch *et al.* (2020) predict inflation variables using factor-augmented VARs (FAVAR), time-varying parameter vector autoregressive models (TVP-VARs), and structural break models. They found that models with heteroscedastic errors performed better than models with homoscedastic errors. Their results also showed that structural break did not enhance the predictability of inflation. Anguyo *et al.* (2020) examine structural changes and measurement of inflation persistence over time using the Uganda data. Using the regression quantile, they find higher levels of persistence after 2006 and during the inflation targeting period. Hegerty (2020) study reveals that no Central and Eastern European members have inflation rate with break point that corresponds to Euro adoption. Results also show that CEE members have multiple breaks with final structural breaks occurring in 2013. Nath and Sarkar (2019) investigate relations between inflation and relative price variability (RPV) using quarterly consumer price index for seventy-four (74) consumption categories in Australia. The results of their empirical research show that a J-shaped non-line relationship between inflation and unexpected inflation exists. Two structural breaks were also identified in inflation-RPV relationship. Gil-Alana *et al.* (2019) study the behavior of inflation rate in Iran from 1992 to 2017, using fractional integration. He documents extremely large degree of persistence in series with an order 2 integration. Orlowski (2017) uses Bai-Perron multiple breakpoint and two-state Markov regime switching tests to investigate the sensitivities of Poland's interest rate to inflation and exchange rate for over two decades. His results reveal a major structural break and regime change at the start of 2002. The break timing reflects de facto inflation targeting effective and credible policy. Other references in this category include Gil-Alana and Mudida (2017), Clemente *et al.* (2017), etc.

Sani *et al.* (2020), Nasir and Vo (2020), Liu *et al.* (2020), Phiri (2020) examine the structural changes of foreign exchange rates in countries and microeconomics variables. Sani *et al.* (2020) examine relationship between exchange rate and interest rate differential for the BRICS countries. Their results show that the exchange rate predominantly responds asymmetrically to the interest rate differential in four out of the five countries examined. Nasir and Vo (2020), using the monthly data from October 1976 to September 2017, investigate implications of Inflation Targeting (I.T.) for the exchange Rate Pass-Through (ERPT) to inflation and trade balance for New Zealand, UK, and Canada. They employed the TVSVAR framework, and their result show a time-variation in the ERPT to inflation and trade balance in the three countries. Liu *et al.* (2020) examine the relationship between the US exchange rate and crude oil prices within the structural break detection context. Results reveal that crude oil prices shocks have both immediate and short-term effect on exchange rate movements which are emphasized during the confidence intervals of structural breaks. Phiri (2020) investigates the impacts of two structural events on exchange rate-equity returns nexus for four (4) Johannesburg Stock Exchange (JSE) indices using the nonlinear autoregressive distributive lag (ARDL) cointegration.

A monthly sample data was collected from 2000 to 2017 and the empirical analysis shows that sub-periods correspond to breaks caused by crisis and the use of new trading platform. Their results also suggest that prior to the crisis, exchange rates appreciations cause stock returns. But depreciations show to unlikely cause stock returns to decrease. Other references include Jeelani *et al.* (2019) who study the relationship between India's macroeconomic factors that affect exchange rate (ER) (INR/USD). Data such as ER, GDP, inflation, interest rate (IR), FDI, money supply, trade balance (TB) and terms of trade (ToT) were collected from the RBI website. The study investigates whether there is any structural break with the application of the Chow's Breakpoint Test. Multiple structural breaks were found between 2003 and 2009 which explained the fact that volume of crude oil imported by India is high, and oil price rise led to a deficit in TB which caused a structural change.

Relationship between structural breaks and revenue is another growing strand in literature. Gil-Alana *et al.* (2019) analyze the structural pattern of Brazilian tourism revenue over the period of 20 years. Results show that benefits obtained from tourism revenue can jeopardize the economic structural problems reflected in currency fluctuation. Kumar *et al.* (2019) investigate the effects of tourism industry on the economic growth of Fiji over a period from 1975 to 2015, using a neoclassical and autoregressive distributed lag (ARDL) bound framework while accounting for structural breaks. The short-run and long-run results reveal that 1% increase in visitor's arrival contributes with about 0.20% and 0.13% to the per capita income, respectively. Min *et al.* (2019) test the structural break of visitor's arrival to Taiwan from China, Japan, the USA and Hong Kong. The Bootstrap with multiple structural break framework is used to model the Taiwan's four inbound time series. They document that the severe acute respiratory syndrome (SARS) outbreak impacts the Taiwan's four major inbound markets. Stauvermann *et al.* (2018) explore the relationship between tourism, exchange rate and the economic growth in Sri Lanka from 1980 to 2014. They employ the Augmented Solow and ARDL framework for the empirical analysis. Their results reveal a long-run relationship among tourism, exchange rate, capital per worker and output per worker. In addition to investigating the structural breaks in the tourism industry, Amiraslany *et al.* (2019) examine structural breaks in biased estimation and forecast errors in GDP series of Canada against the USA. Their result suggests a structural break for Canadian gross domestic product (GDP) when there was a switch from the Standard Industrial Classification system (SIC) to the North American Industry Classification (NAIC) System. Their results also reveal that failure to identify in-sample breaks may adversely affect the model's out-of-sample forecast.

One of the major concerns of many scientific researchers and policy makers is whether Twitter's posts and sentiments influence stock market movements. Thus, huge volume of literature has been documented in this strand. Urlam *et al.* (2020) employ the Long Short-Term Memory (LSTM) neural networks to predict and analyze stock market data. Their results confirm that longer horizon prediction is more useful than the shorter horizon prediction. Their study also compares sentiments analysis and the predicted stock value, and the results reveal that the two are similar. Emotions also show to affect the future of stock prices. Ajjoub *et al.* (2020), Brans and Scholtens (2020), Klaus and Koser (2020), Ge *et al.* (2019) examine the impact of presidential tweets on stock prices. Their results show that President Donald Trump's tweets impact the stock prices, increase trading volume and volatility. Positive tweets were shown to have a pronounced positive impact on the stock price. Besides, negative and neutral tweets have little or no effect on the stock market. Reboredo and Ugolini, (2018) investigate the effects of Twitter sentiment and sentiment mood on stock returns, trading volumes, and volatility for renewable energy stocks. They document that Twitter sentiment has no impact on stock market activities, but Twitter sentiment divergence is shown to generate feedback effects on volatility and trading volumes.

Chahine and Malhotra (2018), Reed, M. (2016) in their studies also examine the impact of social media on the stock market. While the former finds significant market reaction around Twitter activities for subsample of firms contaminated by corporate announcements but not for full sample. The latter empirical results show that sentiment impacts stock prices, particularly, S&P 500 and the Dow Jones Industrial Average. Guijarro *et al.* (2019) investigate whether Twitter sentiment impacts the financial market liquidity in S&P500 Index. Their results find that the investors' mood had little influence on the spread of the index. Other literature references include: Groß-Klußmann (2019), Wu (2019), Shelar and Huang, (2018).

However, our study seeks to investigate the impact of companies' Twitter posts and "likes" on its stock liquidity in the presences of structural changes due to global pandemic. And to the best of our knowledge, no previous study exists in this direction of research. We employ Andrews-Ploberger (1994) and Andrews-Quandt Tests, which allow for the presence of structural break in linear model to examine the US internet Dot-com companies structural break date in stock liquidity using Amihud (2002) liquidity proxy, as well as the impact of Twitter posts for the different sub periods. We found that for nearly all the companies examined, the structural breaks captured are significant. Our results also reveal that neither the Twitter's posts nor "like" appear to influence investors' ability to exchange an asset for cash.

HYPOTHESES DEVELOPMENT

Many previous studies such as Affuso, E., Lahtinen, K.D. (2019), Zhang, X., Fuehres, H., Gloor, P.A. (2012), Vanstone, B.J., Gepp, A., Harris, G. (2019), Makrehchi, M., Shah, S., Liao, W. (2013), Sul, H.K., Dennis, A.R., Yuan, L. (2014), etc., reveal that Twitter sentiment impacts stock price returns. And that there is a strong link between social media and stock returns. There are other studies that document company-initiated news via Twitter leads to the improved liquidity of that company's stock. That is why one of our aims is to test the following hypotheses on the US internet Dot-com companies stock market:

H1: Twitter posts from specific US internet Dot-com companies increases its Stock liquidity

H2: Twitter likes from specific US internet Dot-com companies increases its Stock liquidity

METHODOLOGY AND DATA

The daily stock data used in this study is obtained primary from Yahoo! Finance (http://finance.yahoo.com/). Then a total of 571,499 and 20,912,993 English language tweets and 'likes' from the twelve (12) US internet Dot-com companies examined were collected for the period from September 4th, 2019. to April 1st, 2020. Information on companies' tweets and 'likes' were accessible via https://popsters.com/ website's application programming interface (API). In 2012, Twitter introduced the addition of a cashtag sign to stock tickers to stress on the stock being referred to. For example, Microsoft's tweets were query by $MSFT, Facebook Tweet query by $FB, Apple by $AAPL, etc. Therefore, we used the cashtag ($) preceding the internet Dot-com companies' ticker symbols to search for each companies' Twitter information, such as tweets, likes, messages, retweets, etc.

To avoid noisy data, we cleaned all ‘spam’, duplicated tweets, and other irrelevant tweets associated with datasets. ‘Like’ is a function on many social media platforms which indicates engagement or validation with a piece of content, such as message. According to Cabellon and Ahlquist (2016), like is a form of external validation for social media posts. And the more ‘likes’ a post gets, the more positively the user is perceived.

Table 1 shows that Amazon.com company, an American multinational technology company based in Seattle which focuses on e-commerce, cloud computing, digital streaming, and artificial intelligence, had the biggest revenue of $280.50 billion, market capitalization of $920.22 with 798000 employees in the US in 2019 fiscal year. The Facebook.com company also has the highest numbers of tweets and the corresponding ‘likes’ as shown in Table 2. While Table 2 also shows Twitter data and the search features, Table 3 describes the companies’ stock data used in our analysis. The statistical property for variables such as liquidity, stock volume, firm size, and stock returns were examined in our pre-empirical analysis. With exception of stock returns, each variable appears to be a standard normal distribution with a mean of zero and standard deviation of 1, see Table 3. The standard normal distribution is centered at zero and the measurement of the degree of deviates from the mean is given by the standard deviation. The interquartile range (IQR) as a measure of dispersion indicates that our stock data are not spread out. This is evidence in the 25th and 75th quartile scores.

Table 1. Large International Internet Companies located in US., ranked by total revenues and market capitalization for their respective fiscal years ended on or before March 31, 2019.

Rank	Company Name	Revenue ($B)	FY ending	Nos. of Employee	Market Cap ($B)	Headquarters Location	Year Founded
1	Amazon	$280.50	2019	798000	$920.22	Seattle, USA	1994
2	Google	$161.80	2019	118,899	$921.14	Mountain View	1998
3	Facebook	$70.69	2019	45,000	$585,37	Menio Park, USA	2004
4	Tesla	$24.58	2019	48,016	$75.72	Palo Alto, USA	2008
5	Netflix	$20.16	2019	8,600	$141,98	Los Gatos, USA	1997
6	PayPal	$17.77	2019	23,200	$126.88	San Jose, USA	1998
7	Salesforce.com	$17.10	2019	49,000	$161.71	San Francisco	1999
8	Booking Holdings	$15.06	2019	26,400	$85.06	Norwalk, USA	1996
9	Expedia	$12,07	2019	25,400	$15.42	Bellevue, USA	1996
10	Adobe	$11.17	2019	22,634	$149.30	San Jose, USA	1982
11	eBay	$10.80	2019	13,300	$28.74	San Jose, USA	1995
12	Wayfair	$09.13	2019	16,983	$08.50	Boston, USA	2005

Note:
Revenue: Annual revenue of company in USD billion in previous fiscal year
FY: Company's fiscal year
Employee: Number of employees of company
Market Cap.($B): Market capitalization as of March 2019 in USD billion
Company: Name of the international company with Headquarter in USA
Headquarter: Location of company's headquarters

Table 2. Companies and Twitter Statistics(Dot.Com) Some Ranked US. Largest Internet

Rank	Company Name	Twitter Features		Twitter Data		
		Stocks Tickers	Search Keywords	Total Tweets Collected	Tweets After filtering	Like Tweets
1	Amazon.com, Inc.	AMZN	$AMZN	121007	92883	172416
2	Alphabet Inc, Class A.	GOOGL	$GOOGL	96123	61803	889104
3	Facebook, Inc.	FB	$FB	179023	156283	7557101
4	Tesla, Inc.	TSLA	$TSLA	156115	124084	483837
5	Netflix, Inc	NFLX	$NFLX	88324	62239	1976294
6	PayPal Holdings, Inc.	PYPL	$PYPL	44997	17394	739551
7	Salesforce.com, Inc.	CRM	$CRM	9768	1115	353498
8	Booking Holdings	BKNG	$BKNG	18765	11607	576023
9	Expedia, Inc.	EXPE	$EXPE	16664	10731	1122085
10	Adobe, Inc.	ADBE	$ADBE	21864	12284	2072187
11	eBay, Inc.	EBAY	$EBAY	32765	16254	2595924
12	Wayfair, Inc.	W	$W	11087	4822	374973

Data Transformation by Standardization

Using a sample of the US internet Dot-com companies, we examine whether these companies' posts are reflected in its stock liquidity for the period observed. And whether structural break affects this relationship. The downloaded data for these companies varies in sizes. Therefore, there is the need to provide equal weight for these variables in our experiments, hence the need for data standardization. Many notable authors, such as Bijl *et al.* (2016), Nisar and Yeung (2018), Kim *et al.* (2019), etc., have applied standardization transformation in their research. This is also referred to as the z-score. The formula in equation 1, shows the x and mean dataset at the numerator and standard deviation at the denominator of the equation. Defined as:

$$SV_t = \frac{X_t - \frac{\sum_{i=1}^{n} X_i}{n}}{\sigma_x} \tag{1}$$

Where:

SV_t indicates the standardized values, X_t indicates the raw datasets and σ_x represents the standard deviation of the dataset

Companies' Stock Liquidity Measure

Liquidity is seen as an elusive concept. This is because it encompasses many observed transaction properties on the markets. Therefore, there is an array of liquidity measures employed by empiricists and policy makers, etc., that take into account different liquidity aspects. However, in our research paper, we employed Amihud's (2002) illiquidity ratio, and then obtained the liquidity measure as the inverse of the ratio. Hur and Chung (2018) also applied similar methodology in their study. Thus stated

$$Illiquidity = \frac{1}{l_t}\sum_{i=1}^{l}\frac{|R_t|}{TV_t} \tag{2}$$

Where:

l_t denotes the number of daily observations of stock i in day t.

R_t denotes the market returns, V_t denotes trading volume, and P_t shows the stock price.

Tests for Single Structural Change with Unknown Change Point

We employ Andrews-Ploberger (1994) and Andrews-Quandt structural break model to examine whether regime changes have broken down the stability of the relationship between companies' tweets and its stock market liquidity. The Quandt (1960) and Andrew (1993), now popularly known as Quandt-Andrews breakpoint test tests a specific sample for an unknown structural breakpoint. The Chow's single breakpoint test which performs at every observation between two break points, or observations, τ_1 and τ_2 is the idea behind the Quandt-Andrews test. The k test statistics from the Chow tests are put together into a single test statistic against the null hypothesis of no breakpoints between τ_1 and τ_2.

With the assumption that m or λ is unknown, Quandt employs the LR statistic $H_0 : \gamma = 0$ against $H_1 : \gamma \neq 0$.

This is the maximal $F_n(\lambda)$ statistic over range of break dates m_0, ...,m_1:

$$QLR = \max_{m \in [m_0, m_1]} F_n\left(\frac{m}{n}\right) = \max_{\lambda \in [\lambda_0, \lambda_1]} F_n(\lambda) \tag{3}$$

Where:

$\lambda_i = \frac{m_i}{n}$ = trimming parameters, $i=0,1$

QLR is also the Andrews' *sup-F* statistic

The break data m and break fraction λ are estimated using $\hat{m} = arg\ \max_m F_n\left(\frac{m}{n}\right)$ and $\hat{\lambda}_1 = \hat{m}/n$ respectively.

Since we have no knowledge of the break data, we set our trimming parameter $\lambda_0 = 0.15$.

Whilst Andrews-Quandt test uses as the maximum of the LM statistics, Andrews-Ploberger uses the average of the Chow breakpoint statistics $F_n\left(\frac{m}{n}\right)$ to compute the QLR statistic.

Therefore

$$ExpF_n = In\left(\frac{1}{m_2 - m_1 + 1}\sum_{t=m_1}^{m_2} exp\left(\frac{1}{2}k.F_n\left(\frac{t}{n}\right)\right)\right) \quad (4)$$

$$AveF_n = \frac{1}{m_2 - m_1 + 1}\sum_{t=m_1}^{m_2} k.F_n\left(\frac{t}{n}\right) \quad (5)$$

k = Number of regressors being tested

The critical P-values given in Andrews and Ploberger can be computed using Hansen (1997) techniques or approximations. The distribution of these statistics degenerates at the beginning or when it approaches the end of the equation. To compensate for this behavior, we trim or exclude the first and the last observations by 15%. That is, the same numbers of observations are removed from the beginning and the end of the estimation sample.

RESULTS OF EMPIRICAL ANALYSIS

We study the impact of twitter on the US internet Dot-com companies in the presence of unknown structural breaks. A sample of twelve (12) top companies of US internet Dot-com companies were used for our analysis for the period from September 4th, 2019 to April 1st, 2020. As mentioned earlier in section 3.3, we employ the methodological framework of Andrews-Ploberger (1994) and Andrews-Quandt structural break model to analyze whether structural change influences the relationship between company's tweets and its stock liquidity. Figure 1 in Appendix A illustrates the plots of natural log stock liquidity for the twelve (12) US internet Dot-com companies. The graph shows the various structural breaks for each company. Although the COVID-19 started late, i.e., September - December (Li *et al.* (2020), Yongchen *et al.* (2020), Lone and Ahmad (2020)), Table 4 and Figure 1 show that the pandemic caused a major structural break for the top US internet Dot-com companies at different break points. However, most of these breaks occur between November 2019 to March 2020. In our analysis, we applied five (5) variables – stock liquidity, stock returns, volumes, firm size, tweets and likes. The stock liquidity as an internal variable, tweets and likes as external variables, and the stock returns, volumes, and size as the control variables.

Apart from revealing the major structural break date, our study also examines the sub-period before these breaks, precisely September 4th, 2019. Table 5 shows the empirical results of the companies' tweets and likes on their stock liquidity before the major structural break. Our results reveal that most US internet top companies' tweets and 'likes' do not to influence their stock liquidity rate for the period examined. Specifically, only Adobe, Expedia and PayPal Holding companies' tweets appear to influence their stock liquidity. These influences are very weak, negatively significant at 10% levels and do not boost firm values during pre-structural break periods, see Table 5. This means that these few companies appear to have small numbers of orders to buy and sell on the stock market. It is argued that increase in stock liquidity, increases firm values. This is due to the fact that assets are discounted at a lower cost of capital when there is an improvement in stock liquidity. However, almost all companies' stock volume is shown to impact their stock liquidity. With five (5) of these companies actually have their stock volume increase companies' values.

The values of R squared, and R adjusted are low, but they are reported in Heteroscedasticity-Consistent (Eicker-White) Standard Errors. Hence, the results estimates are consistent. Our analysis does not confirm the study hypothesis of H1 and H2 that companies' tweets and likes increase the companies' stock liquidity. Some companies' stock liquidity has also shown to react to firm sizes in different behavior (increase or decrease).

Table 4. Andrews Ploberger (1994) and Andrews - Quandt Structural Break Tests

Firms	Andrews-Quandt		Resid. Analysis		Andrews-Plober.		Resid. Analysis		Structural Dates	
	Test	P-Val	Test	P-Val	Test	P-Val	Test	P-Val	Break Date	Resid. Date
ADOBE	74.013	0.000	1.006	0.998	33.170	0.000	0.069	1.000	2019:12:19	2019:12:20
AMZN	67.152	0.000	0,757	1.000	30.043	0.000	-0.237	1.000	2020:02:26	2020:02:27
BKNG	61.763	0.000	0.850	1.000	28.481	0.000	-0.078	1.000	2020:01:16	2020:01:16
CRM	34.321	0.222	0.804	1.000	14.005	0.197	-0.216	1.000	2020:12:10	2019:12:10
EBAY	22.059	0.933	0.381	1.000	9.0822	0.848	-0.132	1.000	2019:10:25	2020:01:14
EXPE	50.589	0.004	1.695	0.861	22.326	0.002	0.400	0.529	2019:11:04	2019:11:15
FB	28.147	0.583	1.743	0.850	10.402	0.664	0.566	0.392	2019:11:14	2020:01:22
GOOGL	40.916	0.053	1.878	0.816	17.411	0.037	0.469	0.466	2019:10:29	2019:10:30
NFLX	39.866	0.068	1.407	0.929	17.114	0.043	0.320	0.618	2019:11:19	2019:11:19
PYPL	27.284	0.643	0.770	1.000	10.518	0.646	0.309	1.000	2020:01:20	2020:01:17
TSLA	110.002	0.000	0.495	1.000	50.395	0.000	0.549	1.000	2020:03:03	2020:03:03
W	100.131	0.000	2.348	0.700	45.555	0.000	0.589	0.377	2019:10:15	2019:10:15

Note:

The Andrews-Quandt test uses as its test statistic, the maximum of the LM statistics, while Andrewe-Ploberger uses the geometric mean. These both have highly non-standard distributions. P-values are computed in Hansen (1997) approximations.

However, empirical analysis in Table 6 describes the results using estimation by Least Squares with Heteroscedasticity-Consistent (Eicker-White) Standard Errors, the impact of tweets and likes on stock liquidity after post-structural break. The structural break points are at different dates with different sample sizes. Companies' tweets and likes are shown to have mix results on companies' stock liquidity. Preponderance of companies' tweets and likes also appears to influence their stock liquidity post-structural break. Nevertheless, this influence tends to be negative, which indicates that most of the companies examined appear to have small numbers of orders to buy and sell on the underlying market. Conversely, tweets from PayPal Holdings, Inc; Booking Holdings; eBay, Inc. and Wayfair, Inc. appear to have created large numbers of orders to buy and sell in the underlying market during post-structural break. This large numbers of order to buy and sell increase the probability that the highest prices a buyer is willing to pay and the lowest price a seller is happy to accept converge or move closer together. However, our empirical analysis in Table 6 also shows that Tesla, Salesforce.com, Expedia, and Adobe tweets do not influence the stock liquidity, as the estimation coefficients are not statistically significant. Besides, preponderance of investors validation of companies' tweets with the use of likes also shown to be related to the stock liquidity, i.e., the Tesla, Inc. and Netflix, Inc.

With the mix results of the influence of 'likes' and tweets on companies, our stated research hypotheses of H1 and H2, that tweets and likes from US internet Dot-com companies increase their stock liquidity, are partly fulfilled. In addition, our estimation results are consistent with the standard errors.

Table 7 shows the estimation of a relationship between companies' stock liquidity and some of the activities, such as tweets and likes, performed at their official twitter accounts. We examine these relations using the full sample size of 151 of our experiment without taking into consideration the possible impact of the structural break. The empirical result reveals that neither the companies tweet nor the 'likes' impact on stock liquidity. However, companies' stock volume shows to influence stock liquidity. This impact does not increase firm values as shown by majority of companies examined. Our results estimates are in robust standard errors.

Robustness Check

According to Andrew and Ploberger (1994) when checking the robustness of our estimated test results, Andrew-Quandt breakpoint test is used to estimate the breakpoint of companies' stock liquidity. The P-values of these results as well as the residual analysis are shown in Table 4 and Figure 2. It is indicated that there are significant break points for TSLA, W, EXPE GOOGL, NFLX, ADOBE, AMZN, and BKNG US internet Dot-com companies. However, our analysis reports that the break points in CRM, EBAY, FB and PYPL companies show no significant impact on stock liquidity. Table 4 also shows the residual break points analysis of the stock liquidity with respect to the twitter data. The reported residual structural break dates show to be exact or very close to dates of Andrews-Ploberger (1994) and Andrews-Quandt estimated structural break dates. The Andrews-Quandt and Andrews-Ploberger residual tests and its p-values confirmed the residual analysis to be statistically not different from zero. This analysis points out that our results on the changes of stock liquidity are robust to the break point selection. Nguyen *et al.* (2017), Chuen and Gregoriou (2014), etc., have also employed this approach.

CONCLUSION

This paper examines the relationship between Twitter posts and stock liquidity for the US internet Dot-com companies in the presence of structural breaks. Our study provides an in-depth analysis of this relations for twelve (12) different US stock index, over a period of seven (7) months. Based on the structural break models of Andrews-Ploberger (1994) and Andrews-Quandt which allow for the presence of breaks in a linear model, we have obtained mix results which reveal that nearly all structural breaks recorded are significant. Out of twelve (12) companies' stock liquidity examined, only four (4) companies have stock liquidity structural changes that are non-significant. For investment strategy, this implies that companies' managers and investors have to be company-specific to ascertain whether or not to ignore structural change. In addition to reporting and analyzing the structural change dates for the US internet Dot-com companies, it is crucial to understand the relations between Twitter and companies' stock liquidity so as to figure out whether the extent to which assets are bought and sold quickly at stable prices has any relationship with Twitter posts and likes. Our empirical analysis reveals results for two sub-samples analysis, as well as for full sample experiment.

We find that neither Twitter's posts nor "like" appear to influence investors' ability to exchange an asset for cash. Our results also provide the necessary insight for further research on this study, particularly the use of sentiment analysis. That is, whether sentiments from US internet Dot-com companies' Tweets can explain the dynamics of the stock liquidity considering the structural changes. This will be an interesting future direction.

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Table 5. Estimation by Least Squares with Heteroscedasticity Consistent (Eicker White) Standard Errors for Pre-structural Break Dates

Endogenous variable: Stock Liquidity										
Company	**Constant**	**Tweets**	**Like**	**Returns**	**Volume**	**Firm Size**	**R^2**	**Adj.R^2**	**Break Date**	**Obs.**
Amazon.com, Inc.	-0.0316	0.0772	0.0554	-0.6187	-0.0441*	0.0230	0.201	0.200	2019:9:4-2020:02:26	124
Alphabet Inc, Class A	-0.136***	-0.0110	0.0042	-2.0668*	-0.1680*	0.0693*	0.216	0.164	2019:9:4-2019:10:29	38
Facebook, Inc.	-0.0860	-0.1315	-0.182*	-5.4532	0.0114**	-0.013	0.140	0.120	2019:9:4-2019:11:14	50
Tesla, Inc.	-0.0576	0.0842	-0.029	-0.5139	-0.0816*	0.0978	0.082	0.0803	2019:9:4-2020:03:03	128
Netflix, Inc.	-0.0794	-0.0030	0.1554	0.9023*	-0.0196*	0.000*	0.188	0.175	2019:9:4-2019:11:19	53
PayPal Holdings, Inc.	-0.0670	-0.048*	-0.072	0.0495**	-0.0904	0.115	0.203	0.211	2019:9:4-2020:01:20	97
Salesforce.com, Inc.	-0.088***	-0.0308	-0.0028	0.2794	0.2101**	-0.266*	0.334	02049	2019:9:4-2019:12:10	68
Booking Holdings	-0.107***	0.0927	-0.0239	-2.1898	0.0175*	-0.1044	0.183	0.169	2019:9:4-2020:01:16	95
Expedia, Inc.	4.1493*	0.0094*	0.0329	1.2211	12.958*	-3.3456*	0.427	0.399	2019:9:4-2019:11:04	42
Adobe, Inc.	-0.084***	-0.0257*	-0.0102	-0.484	-0.0337	-0.0075	0.255	0.224	2019:9:4-2019:12:19	75
eBay, Inc.	0.3879	-0.0276	-0.1109	15.056	1.4297*	-0.563**	0.266	0.105	2019:9:4-2019:10:25	36
Wayfair, Inc.	-1.2075	-0.200	0.0432	1.2546	-6.8080	3.5096	0.035	0.025	2019:9:4-2019:10:15	28

Notes:

1. *The symbols ***, ** and * indicates significance at the 1%, 5%, and 10% levels, respectively.*
2. *White heteroscedasticity - consistent (Eicker White) standard errors and covariances are applied to the liner models.*

Table 6. Estimation by Least Squares with Heteroscedasticity-Consistent (Eicker White) Standard Errors for Post - structural Break Dates

Endogenous variable: Stock Liquidity										
Company	**Constant**	**Tweets**	**Like**	**Returns**	**Vol-ume**	**Firm Size**	**R^2**	**Adj.R^2**	**Break Date**	**Obs.**
Amazon.com, Inc.	- 0.6304*	-0.3150*	0.0317*	0.6436*	0.0722*	0.4765	0.1200	0.111	2020:02:26-2020:04;01	25
Alphabet Inc, Class A	0.0363**	-0.1968**	0.1021*	-0.7795*	-0.2202	0.0879*	0.0769	0.0604	2019:10:29-2020:04:01	111
Facebook, Inc.	-0.0120	-0.0841*	0.0628*	-0.8274*	-0.2103	0.0936	0.366	0.2420	2019:11:14-2020:04:01	99
Tesla, Inc.	4.0087	-0.4854	-0.0035	-2.8326	12.574*	-13.435	0.5157	0.2463	2020:03:03-2020:04:01	21
Netflix, Inc.	-0.0779*	-0.0132*	-0.0794	-0.7586	-0.0865	0.000***	0.0903	0.0912	2019:11:19-2020:04:01	96
PayPal Holdings, Inc.	-0.0715	0.1967*	0.172**	0.60130	-0.3210	0.4506*	0.4639	0.3687	2020:01:20-2020:04:01	52
Salesforce.com, Inc.	0.0968**	-0.0430	0.0815*	0.0895*	-0.3788*	0.2653	0.2161	0.1681	2019:12:10-2020:04:01	81
Booking Holdings	0.4992*	1.7922*	0.0335	0.0907**	0.5959*	-0.7008	0.6268	0.5501	2020:01:16-2020:04:01	54
Expedia, Inc.	0.0304**	-0.0932	0.1615*	0.7648	-0.0898	0.0355*	0.2031	0.1973	2019:11:04-2020:04:01	107
Adobe, Inc.	0.0904	-0.1131	0.363*	-0.9992	-.04396	0.4894	0.3721	0.2510	2019:12:19-2020:04:01	74
eBay, Inc.	0.1711*	0.0197*	0.0643	2.9348	-0.0584	-0.2147	0.1708	0.1302	2019:10:25-2020:04:01	74
Wayfair, Inc.	-0.0627	0.0075**	-0.013*	0.1511	-.0.0895	0.0392	0.1453	0.1017	2019:10:15-2020:04:01	121

Notes:

*1. The symbols ***, ** and * indicates significance at the 1%, 5%, and 10% levels, respectively.*

2. White heteroscedasticity - consistent (Eicker White) standard errors and covariances are applied to the liner models.

Table 7. Least Squares Estimation with Heteroscedasticity-Consistent (Eicker White) Standard Errors for Full Sample (4th September 2019 to 1st April 2019)

Endogenous variable: Stock Liquidity									
Company	**Constant**	**Tweets**	**Like**	**Returns**	**Volume**	**Firm Size**	**R^2**	**Adj.R^2**	**Obs.**
Amazon.com, Inc.	0.0015**	0.0226	0.0624	-0.9016	0.2097*	-0.1142	0.1176	0.1124	151
Alphabet Inc, Class A	0.0008	-0.0484	0.0779*	-0.8069	-0.2426	0.1352	0.2491	0.2113	151
Facebook, Inc.	0.0040**	-0.0435	-0.0353	-0.4163*	0.0116**	-0.1846	0.2382	0.1020	151
Tesla, Inc.	0.0030	-0.0103	-0.0523	-0.5360	0.0337	0.1269*	0.2771	0.2130	151
Netflix, Inc.	0.0029*	0.0988	-0.0231	-0.6447	-0.0793*	0.0000**	0.3079	0.2161	151
PayPal Holdings, Inc.	0.0001	-0.0361	0.0529	-0.1514	-0.2618	0.3412	0.4360	0.2997	151
Salesforce.com, Inc.	0.0002**	-0.0342	0.0401	-0.0255	-0.1027**	0.0306	0.1561	0.1027	151
Booking Holdings	0.0013	0.3237	0.0679	0.3706*	-0.1204*	0.1237	0.2146	0.1011	151
Expedia, Inc.	-0.0022	0.0309	0.1100	0.6680	-0.1606	0.1576	0.2646	0.1253	151
Adobe, Inc.	-0.0011	-0.0512	0.1581*	-0.6394*	-0.1737*	0.2003	0.3299	0.2183	151
eBay, Inc.	0.0047*	0.0651	0.0425	3.2092	-0.2267	0.1472	0.1924	0.1543	151
Wayfair, Inc.	0.0022**	-0.0284	0.0270	0.1256	-0.1160	0.0318	0.0314	0.0100	151

Notes:

*1. The symbols ***, ** and * indicates significance at the 1%, 5%, and 10% levels, respectively.*

2. White heteroscedasticity - consistent (Eicker White) standard errors and covariances are applied to the liner models.

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Table 3. Financial Market Variables Summary Statistics (Full Sample)

Panel A	LIQUIDITY					Trading Volume					
Company	Mean	P25	P50	P75	SD	Mean	P25	P50	P75	SD	Obs.
Amazon.com, Inc.	-0.000	-0.277	-0.210	0.138	1.000	0.000	-0.830	-0.369	1.353	1.000	151
Alphabet Inc, Class A	0.000	-0.241	-0.207	0.198	1.000	-0.000	-0.875	-0.370	1.638	1.000	151
Facebook, Inc.	-0.000	-0.496	-0.355	0.941	1.000	-0.000	-0.872	-0.341	1.584	1.000	151
Tesla, Inc.	-0.000	-0.219	-0.176	0.146	1.000	0.000	-0.968	-0.207	1.318	1.000	151
Netflix, Inc.	-0.000	-0.314	-0.263	0.534	1.000	-0.000	-0.804	-0.247	0.946	1.000	151
PayPal Holdings, Inc.	0.000	-0.425	-0.305	0.571	1.000	0.000	-0.988	-0.244	1.447	1.000	151
Salesforce.com, Inc.	-0.000	-0.214	-0.179	0.051	1.000	-0.000	-0.867	-0.326	1.596	1.000	151
Booking Holdings Inc	0.000	-0.182	-0.154	-0.043	1.000	0.000	-0.900	-0.343	1.550	1.000	151
Expedia, Inc.	-0.000	-0.423	-0.303	0.625	1.000	0.000	-0.664	-0.305	0.897	1.000	151
Adobe, Inc.	0.000	-0.200	-0.172	0.129	1.000	0.000	-0.957	-0.304	1.764	1.000	151
eBay, Inc.	0.000	-0.541	-0.340	0.798	1.000	0.000	-0.832	-0.417	1.405	1.000	151
Wayfair, Inc.	-0.000	-0.264	-0.184	0.268	1.000	-0.000	-0.821	-0.347	1.420	1.000	151
Panel B	**Firm Size**					**Market Returns**					
Company	Mean	P25	P50	P75	SD	Mean	P25	P50	P75	SD	Obs.
Amazon.com, Inc.	-0.000	-0.068	-0.231	1.442	1.000	0.000	-0.018	0.0001	0.021	0.019	151
Alphabet Inc, Class A	-0.000	-1.118	0.224	1.607	1.000	-0.000	-0.023	0.000	0.019	0.024	151
Facebook, Inc.	0.000	-1.093	-0.198	1.581	1.000	-0.000	-0.029	0.001	0.023	0.026	151
Tesla, Inc.	-0.000	-1.384	0.066	1.334	1.000	0.005	-0.035	0.004	0.048	0.053	151
Netflix, Inc.	-0.000	-0.804	-0.247	0.046	1.000	0.002	-0.030	0.000	0.035	0.028	151
PayPal Holdings, Inc.	-0.000	-1.234	-0.063	1.426	1.000	-0.001	-0.027	-0.000	0.023	0.086	151
Salesforce.com, Inc.	0.000	-1.031	-0.149	1.525	1.000	-0.000	-0.026	0.001	0.020	0.028	151
Booking Holdings Inc	-0.000	-1.223	-0.153	1.525	1.000	-0.002	-0.027	0.000	0.019	0.054	151
Expedia, Inc.	-0.000	-1.247	0.154	1.341	1.000	-0.006	-0.027	-0.000	0.019	0.047	151
Adobe, Inc.	-0.000	-1.215	-0.118	1.621	1.000	0.000	-0.023	0.001	0.022	0.030	151
eBay, Inc.	0.000	-1.030	-0.282	1.440	1.000	-0.002	-0.032	-1.000	0.020	0.022	151
Wayfair, Inc.	-0.000	-1.186	-0.181	1.520	1.000	-0.005	-1.060	-0.001	0.042	0.068	151

Authors Calculation:

Where; SD, P25,P50, and P75 are the standard deviation 25th, 50th, 75th percentiles respectively.

APPENDIX A

Figure 1. US' Internet Dot.com Companies Liquidity Series and Structural Break Date for the Period 4th September 2019 to 1st April, 2020

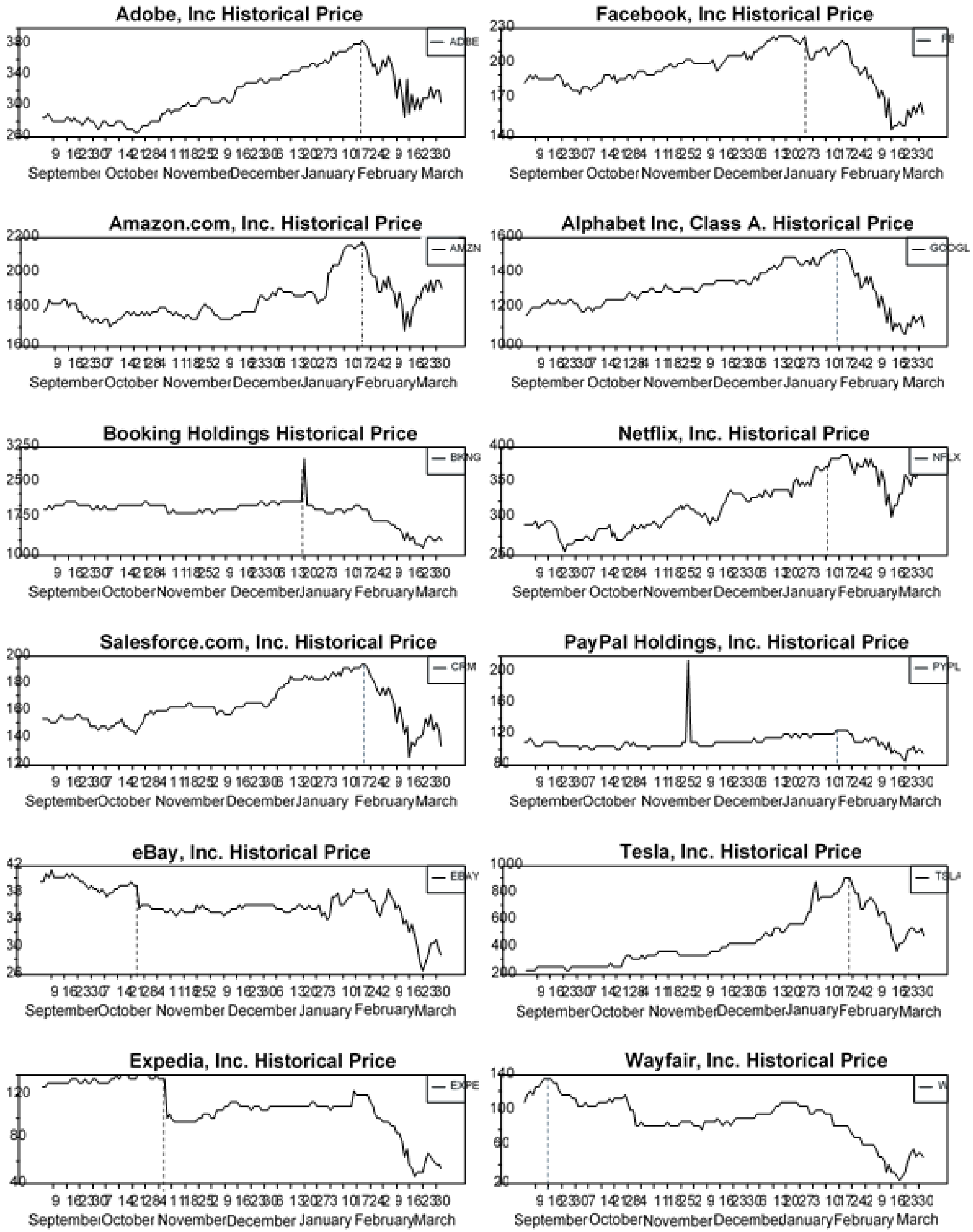
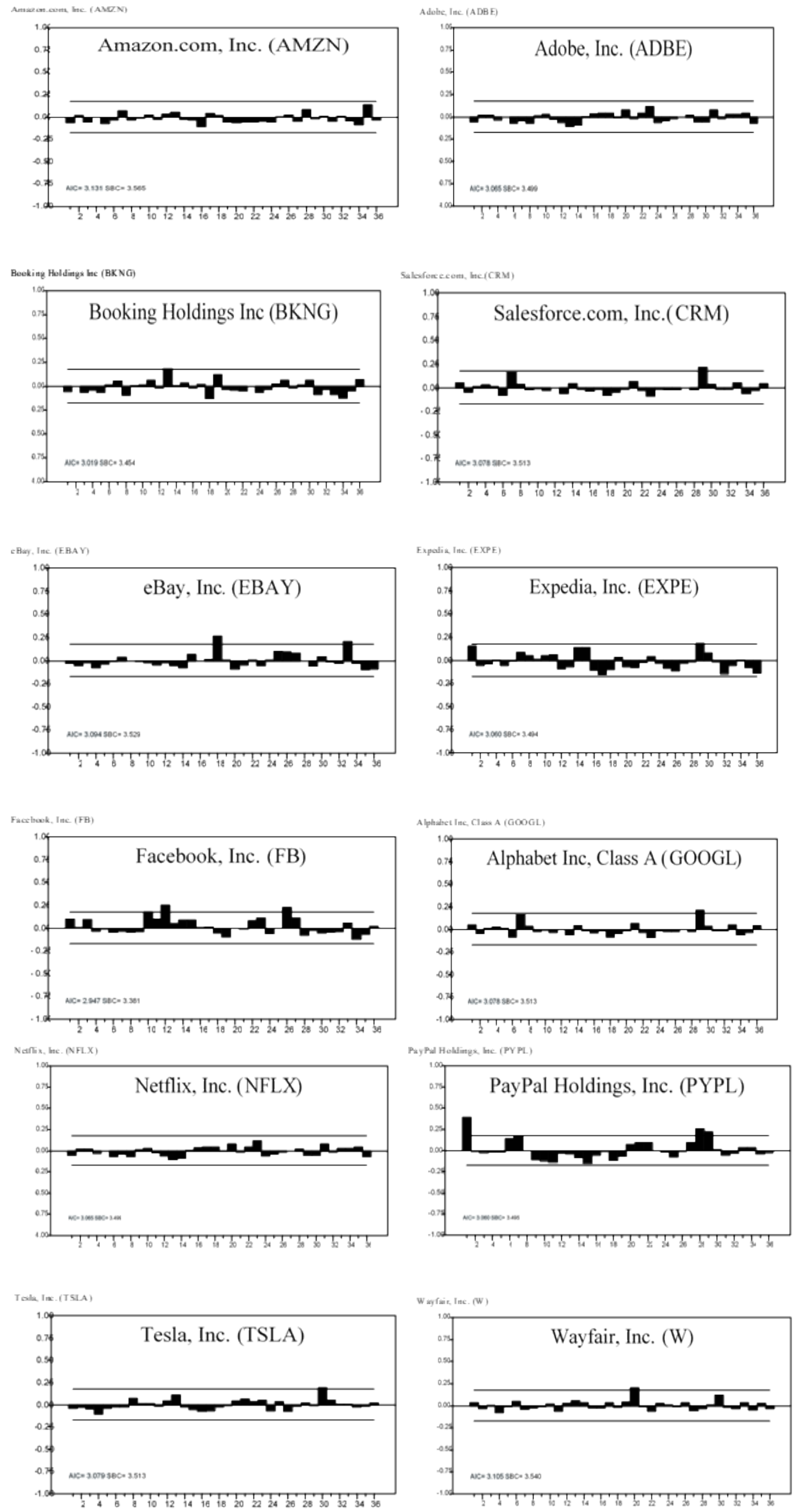


Figure 2. Autocorrelation Analysis on a Series of Residuals for the US Internet Dot-com Companies



STRUKTURNI PREKIDI, TWITER I LIKVIDNOST AKCIJA INTERNET DOT-COM KOMPANIJE: DOKAZI AMERIČKIH KOMPANIJA

Rezime:
Cilj ovog rada je istražiti odnos između Twitter-a i likvidnosti akcija nekih velikih američkih internet Dot-com kompanija u prisustvu nepoznatih strukturnih prekida za period od septembra 2019. do aprila 2020. Koristeći Andrews-Ploberger i Andrews-Quandt strukture modela prekida, identifikujemo glavne strukturne tačke prekida u likvidnosti akcija i otkrivamo da se većina ovih strukturnih promena značajno percipira. Kada smo pregledali podperiode, kao i ceo uzorak, otkriveno je da tvitovi i lajkovi većine kompanija nemaju veze sa likvidnošću akcija. Ovi rezultati pružaju ključan uvid u portfeljsku strategiju kako međunarodnim tako i domaćim investitorima.

Ključne reči:
strukturni prekidi,
Twitter,
akcionarsko društvo,
Andrews-Ploberger,
likvidnost,
režim.