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Herd Behaviour in Financial Markets: Evidence from the Technology Sector

Bachelor's thesis

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Declaration of Authorship

I hereby declare that I compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

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Prague, January 1, 2022

Jaroslav Máca

Abstract

This thesis provides an evidence of herd behaviour in financial markets with an emphasis on the technology sector. The adjusted closing prices for the NASDAQ-100 index constituents are analysed on a daily basis during the period 2011–2020. Regarding methodology, the commonly utilized measures of cross-sectional standard deviation of returns and of cross-sectional absolute deviation of returns are considered. The examination reveals no evidence of herd behaviour, even when filtering trading sessions based on extraordinary market volatility or trading volume. However, a closer look at 2020, in which financial markets movements were heavily affected by the ongoing COVID-19 pandemic, shows that herd behaviour contributed to the sharp and significant crash as well as to the subsequent skyrocketing recovery. Furthermore, this thesis presents an innovative way of using an external factor in regression models. Due to their dominant position, the so-called technology giants are excluded from the US stock market and they newly constitute the world market. This specification reveals that the dispersions of the technology giants are contagiously amplified to the rest of the technology sector. Therefore, investors should be aware of the risks associated with a possible cooling of the entire technology sector following the expected interest rate hikes by the Federal Reserve in the USA.

JEL Classification	G01, G02, G14, G15, G41
Keywords	Herd behaviour, Efficient-market hypothesis, Cross-sectional absolute deviation of returns, Big Tech, COVID-19

Title	Herd Behaviour in Financial Markets: Evidence from the Technology Sector

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Abstrakt

Tato závěrečná práce se zabývá analýzou stádního chování na finančních trzích s důrazem na technologický sektor. Upravené závěrečné ceny složek indexu NASDAQ-100 jsou důkladně studovány na denní bázi v období 2011–2020. Pokud jde o metodiku, uvažují se běžně používané míry průřezové směrodatné odchylky výnosů či průřezové absolutní odchylky výnosů. Zkoumání neodhaluje žádné známky výskytu stádního chování, a to ani při filtrování obchodních dnů s ohledem na mimořádnou tržní volatilitu či objem obchodů. Bližší pohled na rok 2020, ve kterém dění na finančních trzích značně ovlivnila pandemie virové choroby covid-19, ale ukazuje, že stádní chování přispělo k prudkému a výraznému propadu, stejně tak jako k následnému raketovému zotavení. Tato práce dále představuje inovativní způsob použití externího faktoru v regresních modelech. Vzhledem ke svému dominantnímu postavení jsou z akciového trhu v USA vyčleněni tzv. technologičtí obři, kteří nově tvoří světový trh. Tato specifikace odhaluje, že rozptyly technologických obrů jsou zesíleně přenášeny do zbytku technologického sektoru. Investoři by si proto měli být vědomi rizik spjatých s případným ochladnutím celého technologického sektoru po očekávaném zvyšování úrokových sazeb ze strany Federálního rezervního systému USA.

Klasifikace JEL	G01, G02, G14, G15, G41
Klíčová slova	stádní chování, teorie efektivních trhů, průřezová absolutní odchylka výnosů, technologičtí obři, covid-19

Název práce	Stádní chování na finančních trzích: analýza technologického sektoru

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Contents

List of Tables

List of Figures

Acronyms

CAPM Capital asset pricing model

COVID-19 Coronavirus disease 2019

CSAD Cross-sectional absolute deviation of returns

CSSD Cross-sectional standard deviation of returns

EMH Efficient-market hypothesis

NASDAQ National Association of Securities Dealers Automated Quotations

Bachelor's Thesis Proposal

Author	Jaroslav Máca
Supervisor	PhDr. Jiří Kukačka, Ph.D.
Proposed topic	Herd Behaviour in Financial Markets: Evidence from the Technology Sector

Research question and motivation The main goal of my bachelor's thesis lays in the examination of herd behaviour in financial markets with emphasis on the technology sector which has soared since 2011. Herd behaviour is one of the most remarkable cognitive biases which have potential to influence financial markets (Bikhchandani and Sharma, 2000). As Warren Buffet (2011) said: Most people get interested in stocks when everyone else is. The time to get interested is when no one else is. You can't buy what is popular and do well.

However, the previously dominant paradigm seemed to pay no attention to psychological factors. Fama (1970) in the efficient-market hypothesis (hereinafter EMH) assumes homo economicus with a completely rational decision making. In this setup, prices always fully reflect all available information regarding companies' fundamental value with no subjectivity allowed. If this is true, why financial markets suffer from over-reaction periods and other irrational exuberances (Greenspan, 1996)?

Shiller (1981) suggests possible explanation while questioning EHM. The author illustrates on the Great Depression example that investors can be prone, especially when in stress, to make irrational decisions which can lead to financial bubbles and crashes in extreme scenarios. In addition, the noteworthy research in cognitive psychology shows that investors make rather smart, from evolutionary point of view, than rational decisions. Therefore, the intuitive phenomena such as availability, framing, loss aversion and representativeness occur. These errors are usually corrected by the reasoning; though in specific situations remain undiscovered (Tversky and Kahneman, 1974; Kahneman, 1994; Kahneman, 2003).

Contribution Recently published articles indicate that herd behaviour is mostly connected to developing countries (Guney et al., 2017; Kumar et al., 2020). On the other hand, even the most developed economies and the affiliated stock markets are not always free of it (Mobarek et al., 2012). There is a mixed evidence of herd behaviour in financial markets in the United States of America. Although Chiang and Zheng (2010) were not able to detect herd behaviour, Zhou and Lai (2009) successfully pointed out to its presence in different stock markets including NASDAQ.

My bachelor's thesis will continue in researching stock market in the United States of America. Its main focus would be on technology sector as represented by NASDAQ-100 index from 2010 to 2020 as a time period when technology sector pursued record market capitalisation and attracted both the professional and the so-called retail investor attention (Mackenzie, 2021).

I will study to what extent technology giants can be associated to herd behaviour in the rest of the technology sector (Hermann, 2019). It will be also precisely examined how significant role played herd behaviour during 2020 stock market crash and subsequent bull market. To do so, I will test following hypotheses:

#1 There is no statistically significant herd behaviour in the technology sector (as a helicopter view)

#2 Technology giants have no statistically significant association to herd behaviour in the rest of the technology sector

#3 Herd behaviour played no statistically significant role in both 2020 stock market crash and subsequent bull market

Methodology To measure herd behaviour in financial markets, I will try to run the best fitting linear regression model to each described situation. Christie and Huang (1995) propose approach based on computing cross sectional standard deviation of returns, the so-called CSSD methodology. On the other hand, Chang et al. (2000) present slightly modified the so-called CSAD methodology which works with cross sectional absolute dispersion instead. There are both built on the idea that financial markets which exhibit herd behaviour tend to have lower return diversification across individual stocks.

The impact of the technology giants on the rest of the sector will be examined using modified version with regards to an open system (Economou et at., 2011). I will also consider upgraded formulas which focus on days with extreme trading volume or market volatility to provide more detailed analysis (Tan et al., 2008).

I have pre-selected NASDAQ-100 index as a benchmark while studying listed companies because it consists mainly of well-known technology companies and reflects market movements in one of the largest stock exchanges in the world according to its website. I will analyse daily closing prices (and trading volume) from January 2011 to December 2020.

As a dataset, I will use historical data as available on Yahoo! Finance website for given companies and the associated index.

Outline The bachelor's thesis would be divided into following parts:

1. Introduction
2. Literature review
3. Methodology
4. Dataset
5. Hypotheses testing
6. Empirical results
7. Conclusion
8. Further issues
9. References
10. Appendixes

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Author Supervisor

Chapter 1

Introduction

> "*Most people get interested in stocks when everyone else is. The time to get interested is when no one else is. You can't buy what is popular and do well.*"
>
> – Warren E. Buffet, *Berkshire Hathaway*[1]

Predicting stock prices in financial markets can be regarded as challenging task in normal times, not to talk about major shifts caused by unexpected events – stock market bubbles and crashes. Recently, COVID-19 pandemic show that even a submicroscopic virus can hit world stock market up to 34% (Huang *et al.* 2021). However, subsequent fiscal and monetary stimulus contributed to the extremely fast recovery.

Traditional finance sticks to the commonly used approach in economics, assuming the homo economicus. If the role model holds, investors are believed to rationally maximalize utility in a narrow self-interest. Fama (1965) suggests efficient-market hypothesis (EMH) under which prices always "fully reflect" important information. Therefore, market participants and other economic subjects adjust their decision-making while relying on the relevancy of prices in the markets (Fama 1970).

In contrary to that, Shiller (1981) questions the axiom of inherent rationality returning to the analysis of the US stock market during Great Depression (1929-1939). Expected profit, approximated by cumulative dividends, dropped just slightly by cca 20% but stock prices plunged by 89.2% from peak to trough. The findings of "stock market overreaction" are later confirmed by other scholars (Bondt & Thaler 1985). Moreover, Thaler (2016) calls for a mixture of cognitive

[1] For the complete speech delivered by the "Oracle of Omaha" see Annual Meeting 2011

psychology and economics strenghtening the role of a new paradigm; so that becomes Nobel prize laureate "for his contributions to behavioural economics" in 2017 (Earl 2018).

Those advancements in financial theory are backed-up by remarkable evidence provided by research in cognitive psychology (Kahneman 2003; Kahneman & Tversky 1979; Tversky & Kahneman 1974). It is shown that judgement under uncertainty, which investing in stock market inevitably is, can be prone to cognitive biases. The errors come from evolutionary natural tendency to rather smart than logical decision-making (Kahneman 2003). Given limited processing power, one have to stick to just some information; becoming vulnerable especially when in stress.

This thesis enriches literature concerning herd behaviour by providing evidence from the technology sector. Herd behaviour is one of the cognitive biases which can significantly affect stock market (Bikhchandani & Sharma 2000). Herd is formed when individuals supress their own opinions and follow the crowd in the hope of background information behind it. Hence, we have to be aware of the spurious "herding" – rather kind of the rational behaviour as investors independently react in an analogous style on newly published fundamental information (Bikhchandani & Sharma 2000).

The market which exhibits truly psychological herd behaviour suffers from severe shortages. Mainly, such stock market does not reveal true pri1ce information which are prone to diverge from the long-term equilibrium (Devenow & Welch 1996). The ineffiency makes market vulnerable to inflating bubbles and their subsequent sudden bursts (Shleifer 2000). Skyrocketing stock prices in the technology sector work as a reminder of previous bubble in the field. The so called dot-com bubble occured as a result of irrational exuberance in the late 1990s when NASDAQ-100 rise about 400%. Then, it crashed by 86% by October 2002 (Morris & Alam 2012).

Nowadays, the analysts argue if stock prices in technology sector reflect rational growth or signal potential burst of the bubble (Ciolli 2015; Wang 2018a;b). Technology heavy index NASDAQ-100 soared about 450% in the decade from 2011 to 2020 which surpasses the sharp movements from the end of the past millennium. Moreover, the technological giants, actually the largest publicly traded companies in the world, take-off even more spectacularly. Noteworthy, the impressive performance is related to the subscription streaming service and production company of Netflix; one stock traded per \$25 in January 2011 but has skyrocket to \$525 by December 2020. Media report on topic, calling hegemons in the field as "Big Tech" which promotes their uniqueness (Brodie 2013; Dismembering Big Tech 2019; Sandbu 2018). Big Tech are neither just technology innovators nor just successful businesses, they strive to be a part of sociological and political change all over world (Grind *et al.* 2019; What would happen if Facebook were turned off? 2019).

Regarding statistical modelling, commonly used CSAD and CSSD methodologies will be considered (Chang *et al.* 2000; Christie & Huang 1995). Both share the same spirit of which lower dispersions implying investors seek the comfort of the "market consensus". This in fact signal the prevalence of the herd behaviour.

To bring little light into the darkness of financial markets, following hypotheses will be tested:

- #1 There is no statistically significant herd behaviour in the technology sector (as a helicopter view)
- #2 Technology giants have no statistically significant association to herd behaviour in the rest of the technology sector
- #3 Herd behaviour played no statistically significant role in both 2020 stock market crash and subsequent bull market

The rest of the thesis is structured as follows: Chapter 2 provides an overview of the relevant literature. Chapter 3 explains the application of statistical methods. Chapter 4 describes the data. Chapter 5 presents and discusses the results. Chapter 6 concludes the thesis.

Chapter 2

Literature Review

2.1 Traditional finance

The attractiveness of analysing stock prices can be traced back at least to the beginning of 20th century when financial markets were thought to be efficient. Bachelier (1900) suggests market to follow random walk process, under which inherent randomness eliminates the possibility to predict further movements.

Nonetheless, pillars of the modern financial theory come up decades later. In 1960s, two traditional finance cornerstones emerge: capital asset pricing model (Sharpe 1964) and efficient-market hypothesis (Fama 1965). Both share the same considerations of expected utility maximization, market equilibrium, and fundamental analysis.

Following Sharpe (1964), it is acknowledged that uncertainty seems to be an integral part of financial markets which necessitates to incorporate—and quantify—risks into valuation models. Sharpe (1964) suggests that assets in the financial market can be ascribed by the correlation rate with given market benchmark. This measure of the systematic risk, the so-called "beta coefficient", points out how much risky the asset is based on its observed—respectively expected—co-movements with the market index. Given market equilibrium, we can overlook the remaining firm-specific idiosyncratic risk. Further, we assume the existence of an asset with a positive yield and zero risk—e.g. the US Treasury securities—in the model to be able to derive market risk premium. Taken into consideration how much given stock tend to "transcend" market benchmark, it is argued that the riskier stock profile, the bigger is possible profit if bull market, respectively is possible loss if bear market. Therefore, as the market can be affected by miscellaneous unpredictable events, the knowledge of impacts for investor who holds a “catalyst” or an “inhibitor” in portfolio can provide helpful information.

Following Fama (1965), an efficient market is “a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values”. It is also assumed that investors are capable of processing all available information, and that is the reason why prices are said to “fully reflect” the given information set (Fama 1970). Furthermore, it is acknowledged that presumed market with no transaction costs, free access to information and its unanimous interpretation does not correspond to the existing ones. Therefore, the efficiency of the market is said to hold if “sufficient number” of investors behave rationally (Fama 1970). In that case, irrationality is believed to be occasional and cancelled out with other irrational trades.

Depending on the implied dozen of information, Fama (1970) states three versions of the efficient-market theory: weak, semi strong and strong one. In the weak version, only historical prices are considered for that purpose which is similar to the avant-garde study of Bachelier (1900). In the semi-strong version, all publicly available announcements such as annual earnings or stock splits on “micro” level and macroeconomic data or key political news on “macro” level are added to the information set. The strong version then respects both public and private information, which allows even insider trading to be reflected in the stock prices.

The critics of the EMH argue that some investors are able to constantly beat the market (Coval *et al.* 2021). Indeed, the lack of possibility to profit reduce the motivation to trade which could eventually lead to catastrophic market collapse (Grossman 1976). Moreover, Grossman & Stiglitz (1980) argue that such market actually cannot exist. Nonetheless, Fama (1970) assumes that stock prices are unpredictable, meaning, they follow a random walk and nobody can beat the market in the long run.

It is also argued that following price-earnings ratio (P/E) can offer the opportunity for “abnormal” profit to contrarian investors (Basu 1977). Stocks with low P/E are shown to be systematically undervalued as they tend to outperform stocks with high P/E in the US market given time range 1957-1971.

Last but not least, EMH fails to explain price movements during highly volatile periods, especially stock bubbles and their sudden bursts. At these times, investors are believed to behave irrationally driven by emotions as for example greed or fear (Fenzl & Pelzmann 2012).

2.2 Behavioural finance

Taken into considerations drawbacks of traditional finance, the need for theory field relaxing axiom of homo economicus occurs. Shiller (2003) calls for incorporating cognitive psychology into neo-classical economic theory. Behavioural finance can then be regarded as a "study of human fallibility in competitive markets" trying to explain what preferences market participants actually have, which the expected utility theory fails to do precisely (De Giorgi *et al.* 2010; Shleifer 2000). The starting point of such approach is to recognize that investors are not always rational, even though striving to maximize the profit in financial market.

The paradigm rests on two building blocks of limits to arbitrage and psychology (Barberis & Thaler 2003). It is thought that as the arbitrage is accompanied by both risks and costs, prices can diverge from fundamentally reasonable levels. On contrary to that, EMH relies heavily on the ability of arbitrageurs to address mispricing in the financial market. The cycle of boom and crash in financial market may be accepted as natural element at least since the beginning of the 17th century when Dutch tulip bulb mania took place (Fenzl & Pelzmann 2012).

Shiller (1981) questions the axiom of inherent rationality returning to the analysis of the US stock market during Great Depression in the 1930s. Expected profit, approximated by cumulative dividends, dropped about 20% but stock prices plunged by 89.2% from the 1929 peak to 1932 trough. Additionally, the "overreaction" of the US stock market is later confirmed by the work of Bondt & Thaler (1985) extending time period from 1926 to 1982. They test whether past returns can determine further development. It is concluded that "winners" portfolio, created by stocks which made excessive returns prior to "starting months"; have earned about 25% less than "losers" in the subsequent thirty-six months giving rise to the opportunity for contrarian investors.

Regarding irrational exuberances (Greenspan 1996), periodically recurring patterns in financial market are observable as well. The January effect stresses that stock returns in the first month of given year are frequently much higher when compared to the remaining eleven months (Keim 1983). "Sell in May", other archetype observable in financial markets, then warns of usually low returns during summer months compared to period from November to April next year (Bouman & Jacobsen 2002). Investor who would follow the instruction could sell his or her stocks in May and return to the market exactly on Halloween. That is the reason why the phenomenon is also known as the Halloween indicator.

It is concluded that irrationality can be potential reason why prices tend to deviate from fundamentally healthy levels (Hirshleifer 2001). The cognitive biases come from the limited processing power human brain have which make individuals to use heuristics to finalize decisions (Hirshleifer 2001). For example, hesitation towards loss realization which can be further linked to one‘s unwillingness to sell losing stocks but tendency to sell winning stocks (Odean 1999; Shefrin & Statman 1985). In contrast, a rational investor would exhibit the opposite (Badrinath & Lewellen 1991).

Kahneman & Tversky (1979) present the prospect theory focusing on decision-making under risk. The loss aversion and related concepts are illustrated using both monetary and non-monetary experiments. It is shown that individuals are prone to prefer certain profit over mere chance for higher one resulting in the same expected utility; but are prone rather to risk bigger loss in the hope of avoiding it completely than to accept proportional one straightforwardly. Moreover, the positive feelings arising from win of given amount can be negatively balanced even by significantly smaller loss. This is caused by assessing loss and gain perspectives in an asymmetric manner. Individuals also tend to lose contact with the proportions of probabilities if these are small enough, respectively extremely high.

These findings invalidate the expected utility hypothesis, a theory of decision-making under uncertainty within the scope of traditional finance. Other cognitive biases which distort rationality include mental accounting, framing, and overconfidence among others (Ritter 2003). The incorrect beliefs remain often unchanged even when confronted ignoring new information or developing pseudo-arguments (Shiller 1999).

Additionally, numerous remarkable investors stress that their decision-making is massively influenced by other investors (Devenow & Welch 1996). The tendency of individuals to mimic the actions of others, i.e. herd behaviour, is nowadays of particular interest (Bondt *et al.* 2015).

2.3 Herd behaviour (overview)

Herd behaviour is one of the cognitive biases which can significantly affect stock prices in financial market (Bikhchandani & Sharma 2000). It is argued that in extreme cases widespread herding can result in both financial bubbles and subsequent crashes (Chari & Kehoe 2004). Literature defines herd behaviour in several ways but the heart of the matter remains intact. Herd behaviour takes place whenever "everyone doing what everyone else is doing, even when their private information suggests doing something quite different" (Banerjee 1992). Regarding financial market, it can be described by significant correlations in trades due to investors being conscious of and influenced by the actions of others in their decision-making (Bikhchandani & Sharma 2000; Chiang & Zheng 2010).

This thesis follows the definition suggested by Hwang & Salmon (2004): "Herding arises when investors decide to imitate the observed decisions of others or movements in the market rather than follow their own beliefs and information". As already mentioned, the intention to imitate others is the key marker here (Bikhchandani & Sharma 2000).

Herd behaviour can be categorized in several ways. Intentional herding, the truly psychologically one, occurs when individuals disregard private information and blindly follow "market consensus" (Christie & Huang 1995; Devenow & Welch 1996). This can lead to inefficient market outcomes as there is no underlying information for such decision (Bikhchandani & Sharma 2000). Indeed, there is only hope crowd to have access to better information that given investor. Although irrational, the tendency to submit oneself to perceived authority seems to be natural element of the unconscious psyche (Freud 1922; Milgram 1963).

The phenomenon is not limited to retail investors, even though herd behaviour among institutional investors slightly differs. The subject of risk is now transferred to the one's profession, not directly to invested money. Evaluated by comparison to others professionals; the motivation to "consider" their opinions increases—given loss aversion phenomenon—to maintain career reputation (Scharfstein & Stein 1990; Trueman 1994). Otherwise, they would take a risk being considered as lone fools. However, the urge to find extraordinary good investment opportunity which is in the end the only important thing decreases.

In contrary to that, in case of investors who have access to the same information such as release of macroeconomic data or political news; similar trades would imply spurious "herding" (Caparrelli *et al.* 2004). That kind of behaviour is not of our primary interest in this thesis as it is rather the rational decision-making based on fundamental analysis, even though differentiation in analytical work seems to be challenging task at first. Following Gavriilidis *et al.*

(2013), correlation between investors decisions and newly published fundamental information can serve here as a guiding indicator.

Herd is typically being formed by analogy to snowball packing, stressing the importance of the so-called information cascade. Bikhchandani *et al.* (1992) explain why an individual, after observing the actions of other investors, can ignore private information and follow the crowd. Psychological motivation such as external rewards, punishment for those that do not follow the trend, preference for conformity, and communication standardize social behaviour including observed investment decisions. Cascades form rapidly; but are also fragile, given the fact that new information, even with low significance, can easily interrupt them. This "consolidation" allows prices to better reflect fundamental information. Unsurprisingly, markets where information is less accessible, transparent or presents lower quality are more prone to informational cascade to arise (Kim & Nofsinger 2005).

As suggested, herd behaviour is thought to be a possible explanation why prices drive away from their fundamental "fair values" which can lead to market bubbles and crashes in extreme situations (Christie & Huang 1995; Devenow & Welch 1996; Lux 1995; Tan *et al.* 2008). Moreover, highly correlated returns of different classes of assets reduce desired benefits of portfolio diversification (Chiang & Zheng 2010). Nonetheless, herd behaviour can potentially create space for profitable trading strategies (Hwang & Salmon 2004).

2.4 Herd behaviour (specific)

The pioneering study of Christie & Huang (1995) introduces approach based on how the stock returns tend to stick to "market consensus" if herding present. Further, the statistical measure of cross-sectional standard deviation (CSSD) is presented to focus on periods of market stress, namely periods of extremely high and extremely low market returns, when herding is assumed to be more prevalent. Testing herding in the US stock market, Christie & Huang (1995) do not find any evidence within given time range 1925-1988.

Alternative approach is suggested by Chang *et al.* (2000) who use cross-sectional absolute deviation (CSAD) of individual stock returns instead of CSSD. It is argued that according to CAPM, dispersions and market returns follow exactly linear relationship and not only generally increasing one. Therefore, Chang *et al.* (2000) add quadratic term to examine the relationship more precisely; thus the significant and negative quadratic term implies herding violating CAPM assumptions. They study both developed and developing markets during different periods across second half of the 20th century. Regarding US market, no evidence of herding is detected by Chang *et al.* (2000) using CSAD within time range 1963-1997 confirming the results of Christie & Huang (1995). Besides, they document no evidence of herding on the part of market participants in the Hong Kong and partial evidence of herding in Japan. However, for South Korea and Taiwan, the two emerging markets in given sample, significant evidence of herding is found.

The stressful periods do not have to be limited to the bullish or bearish market as proposed by the work of Tan *et al.* (2008) who also consider periods with extreme trading volume and extreme volatility. To do so, upgraded versions of CSAD methodology which enable to capture such market movement are presented. They examine dual-listed Chinese market in Shanghai and Shenzhen; where notably, A-shares are dominated by domestic individual investors while foreign institutional investors occupy B-shares. The findings suggest retail investors are more prone to herd under conditions of rising markets, high trading volume, and high volatility. By contrast, no asymmetry is apparent among institutional investors in B-share market.

Until now, CSAD methodology as proposed by the Chang *et al.* (2000) relies on the assumption of the so-called closed market (Chiang & Zheng 2010). However, a great deal of studies point out that some markets exhibit tendency to herd around superior-and-related markets (Chiang & Zheng 2010; Economou *et al.* 2011; Guney *et al.* 2017; Mobarek *et al.* 2014; Youssef 2020). The novel feature of including the so-called external factor is demonstrated in the work of Economou *et al.* (2011). As a consequence, the assumption of no cross-border effects is relaxed. Regarding the economies of the Southern European countries of Portugal, Italy, Greece, and Spain; a great degree of co-movement in the cross-sectional returns' dispersion across these four markets is found. That means that risks for investors increase as the desired benefits of portfolio diversification are reduced in the region (Economou *et al.* 2011). Moreover, majority of the continental Europe and Nordic countries herd around Germany which is said to take on a dominant role in Europe (Mobarek *et al.* 2014).

More importantly, it is shown that dispersions in the US stock market play a significant role in explaining the herding activity all around the developed and developing countries (Chiang & Zheng 2010; Economou *et al.* 2011; Guney *et al.* 2017). Comprehensive research of Chiang & Zheng (2010) provides evidence that all examined advanced, Asian, and Latin American markets herd around the US market 1988-2009. Moreover, robust evidence that the cross-sectional returns' dispersion in Portuguese, Italian, Spanish, and Greek market exhibits a positive relationship with the lagged squared return on the S&P 500 index (Economou *et al.* 2011). On the other hand, in the work of Guney *et al.* (2017), it is concluded that the herding in African frontier markets—which are not connected by the umbilical cord with the international financial system—is driven by the US and South African markets only on a small number of occasions.

Furthermore, contagion effects are discovered in commodity markets (energy, industrial metals, precious metals, grains food, and livestock). Youssef (2020) extend the literature by conclusion that oil prices and major financial indicators motivate herding in these commodity markets. Regarding herding, the US stock market is also shown to play an important role in the energy and the industrial metals sectors. In addition, Kumar *et al.* (2021) focus on the major commodity markets in the Asia-Pacific region. Noteworthy, they find that herding is more pronounced during periods of high volatility.

Last but not least, major economic crises are thought to emphasize herd behaviour in financial markets. In Europe, herding effect is highly-pronounced during the global financial crisis in most continental countries; while Eurozone crisis affected rather Nordic ones (Denmark, Finland, Norway, and Sweden) (Mobarek *et al.* 2014). Recently, COVID-19 pandemic increase herding in capital markets of Europe as the fear and uncertainty drive less informed crowd to follow the leaders (Espinosa-Méndez & Arias 2021). By contrast, COVID-19 does not amplify herding in cryptocurrency markets which are for their disruptive nature close to the studied technology sector (Yarovaya *et al.* 2021).

Chapter 3

Methodology

3.1 CSSD measure

Christie & Huang (1995) suggest using cross-sectional standard deviation of returns, or dispersion (hereafter CSSD methodology), to study herd behaviour in financial market using statistical modelling. Dispersions indicate how much individual returns differ from the market. If all stocks follow the market, they are equal to zero; otherwise above zero.

Following research in social psychology (Kahneman 2003; Kahneman & Tversky 1979), people are more likely to supress their own belief and blindly follow the crowd in stressful situations compared to the predictible ones. In financial markets, periods with extremely high or low market returns are great examples of stressors which are further taken into consideration (Christie & Huang 1995; Odean 1999; Shefrin & Statman 1985).

According to CAPM, higher absolute market returns would imply increase in individual dispersions due different stock sensitivities (Black 1972). In contrary to that, if investors herd around the "market consensus", individual stock returns would not stray far from market return. Therefore, as the two paradigms come to opposing conclusion, it is possible to test which holds based on the analysis of the already mentioned dispersions. Firstly, we calculate dispersions as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}} \tag{3.1}$$

where $R_{i,t}$ is the observed return of stock i on day t, N is the number of stocks in the market portfolio and $R_{m,t}$ is the cross-sectional average return for given market portfolio on day t.

We have to be careful when interpreting trading sessions with low dispersions, even though this is usually related to investors ignoring prior heterogeneous information, i.e. participating in herd behaviour. However, it is assumed that the inherently tranquil and thus "boring" periods tend to exhibit the same pattern.

To be able to differentiate if dispersions change in outermost market returns compared to normal times, we run following linear regression model:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \tag{3.2}$$

where $CSSD_t$ is the return dispersion at time t. D_t^L is a dummy variable at time t taking on the value of unity when the market return at time t lies in the extreme lower tail of distribution, and 0 otherwise. Similarly, D_t^U is a dummy variable with a value of unity when the market return at time t lies in the extreme upper tail of distribution, and 0 otherwise. To define cut-off areas, Christie & Huang (1995) suggest two options – take both lower and upper tails based on 1%; or take both tails based on 5% criterion instead.

The intercept denotes the average dispersion of the sample excluding the regions covered by the two dummies. Rational asset pricing model would imply significantly positive coefficients for β^L and β^U; while negative estimates of β^L and β^U would be consistent with the presence of herd behaviour.

Last but not least, there are problems related to application of CSSD methodology, e.g. too large effect of outliers (Economou *et al.* 2011), lower sensitivity to detect correctly (Chang *et al.* 2000) and no possibility to add external factor into equation. Therefore, we consider also different approach to enhance credibility of the derived results.

3.2 CSAD measure

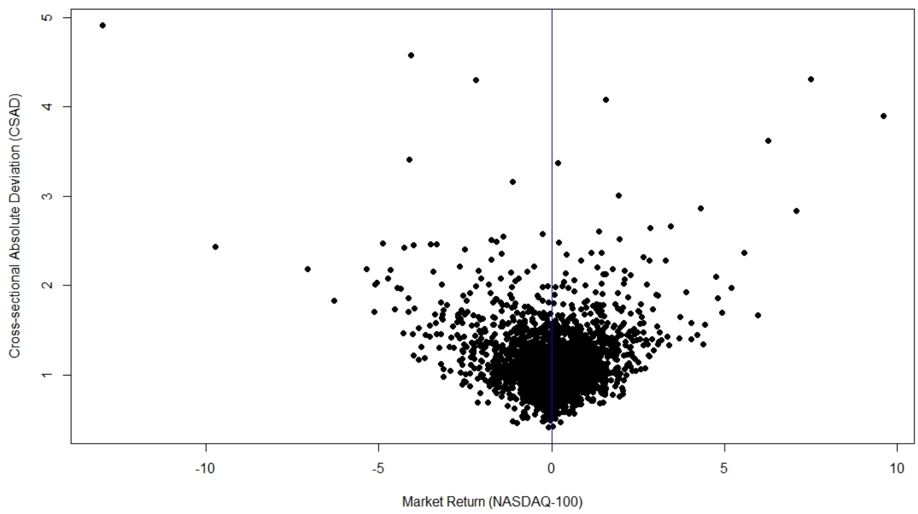
Chang *et al.* (2000) presents alternative approach how to detect herd behaviour in financial markets, even though its spirit remains inspired by the work of Christie & Huang (1995). Mainly, the cross-sectional absolute deviation of returns, dispersions (hereafter CSAD methodology) is used instead of CSSD. This is given by:

$$CSAD_t = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N} \tag{3.3}$$

where $R_{i,t}$ is the observed stock return on firm i on day t, N is the number of stocks in the market portfolio and $R_{m,t}$ is the cross-sectional average return on day t.

The nature of the already mentioned is well documented in the Figure 3.1.

Figure 3.1: Relationship of daily $CSAD_t$ and market return $(R_{m,t})$ for NASDAQ-100 index (3/1/2011 – 30/12/2020)



Source: Author's own computations.

It can be shown that, according to CAPM, relationship between dispersions and market return is not only generally increasing but specify its exactly linear form. In contrary to that, if investors start to mimic actions of others, the linearity assumption would intuitively no longer hold (Chang *et al.* 2000).

Further, we illustrate the relationship between CSAD and market return using CAPM as proposed by Black (1972):

$$E_t(R_i) = \gamma_0 + \beta_i E_t(R_m - \gamma_0) \tag{3.4}$$

where γ_0 is the return on the zero-beta portfolio, β_i is the time-invariant systematic risk of stock i from total of N stocks, for given time t, of the equally-weighted portfolio. Hence:

$$\beta_m = \frac{1}{N}\sum_{i=1}^{N} \beta_i \tag{3.5}$$

The absolute value of the deviation (AVD) of the expected return for stock i on day t can be expressed as:

$$AVD_{i,t} = |\beta_i - \beta_m| E_t(R_m - \gamma_0) \tag{3.6}$$

Hence, we can define the expected cross-sectional absolute deviation of stock returns (ECSAD) on day t as follows:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} AVD_{i,t} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m|E_t(R_m - \gamma_0) \tag{3.7}$$

The increasing and exactly linear relationship then holds if following conditions are met:

$$\frac{\partial ECSAD_t}{\partial E_t(R_m)} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m| > 0 \tag{3.8}$$

$$\frac{\partial^2 CSAD_t}{\partial E_t(R_m)^2} = 0 \tag{3.9}$$

However, herd behaviour usually results in non-linearly increasing or even decreasing relationship. Therefore, Chang *et al.* (2000) add quadratic term to model such non-linear quadratic relationship using proxy variables for the unobservable ones. Finally, we get following regression model:

$$CSAD_t = \alpha + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t \tag{3.10}$$

where the $CSAD_t$ is the cross-sectional absolute deviation of returns on day t, while $R_{m,t}$ is the cross-sectional average return on day t. More importantly, the presence of a negative and significant β_2 parameter is an indication of herd behaviour in our model.

3.2.1 CSAD measure with respect to extreme market volatility

Upgraded CSAD methodology versions will be considered as the investors seek the comfort of consensus opinion mainly during abnormal market conditions. Firstly, periods with extreme market volatility will be studied as this signal potential turbulence. Following Tan *et al.* (2008), we define volatility to be high if higher than its 30-day moving average; to be low if lower than its 30-day moving average.

As a result, the regression models to be estimated:

$$CSAD_t^{\hat{\sigma}^2,HIGH} = \alpha + \beta_1^{\hat{\sigma}^2,HIGH}|R_{m,t}^{\hat{\sigma}^2,HIGH}| + \beta_2^{\hat{\sigma}^2,HIGH}(R_{m,t}^{\hat{\sigma}^2,HIGH})^2 + \varepsilon_t \tag{3.11}$$

$$CSAD_t^{\hat{\sigma}^2,LOW} = \alpha + \beta_1^{\hat{\sigma}^2,LOW}|R_{m,t}^{\hat{\sigma}^2,LOW}| + \beta_2^{\hat{\sigma}^2,LOW}(R_{m,t}^{\hat{\sigma}^2,LOW})^2 + \varepsilon_t \quad (3.12)$$

where the superscripts $(\hat{\sigma}^2, HIGH)$ and $(\hat{\sigma}^2, LOW)$ refer to high return volatility and low return volatility. Noteworthy, volatility as defined by $\hat{\sigma}^2$ is calculated as the square of the portfolio return in period t. To secure robustness of the results, modifications running 7-day, 90-day and 180-day moving averages are considered as well.

3.2.2 CSAD measure with respect to extreme trading volume

Bearing a resemblance to previous example; periods with extreme trading volume will be tested as well. Following Tan *et al.* (2008), we define trading volume to be high if higher than its 30-day moving average; to be low if lower than its 30-day moving average.

As a result, the regression models to be estimated:

$$CSAD_t^{V-HIGH} = \alpha + \beta_1^{V-HIGH}|R_{m,t}^{V-HIGH}| + \beta_2^{V-HIGH}(R_{m,t}^{V-HIGH})^2 + \varepsilon_t \quad (3.13)$$

$$CSAD_t^{V-LOW} = \alpha + \beta_1^{V-LOW}|R_{m,t}^{V-LOW}| + \beta_2^{V-LOW}(R_{m,t}^{V-LOW})^2 + \varepsilon_t \quad (3.14)$$

where the superscripts $(V-HIGH)$ and $(V-LOW)$ refer to high trading volume and low trading volume. To secure robustness of the results, modifications running 7-day, 90-day and 180-day moving averages are considered as well.

3.2.3 CSAD measure with respect to external factor

Previous versions derived from the basic CSAD methodology rely on axiom that national stock exchange is a closed system which is not influenced by foreign factors. However, it is argued that three crucial phenomena; media, globalisation, and digitalization enable investors to make instant and informed decision in different stock markets (Koren 2003; Manyika *et al.* 2016).

This has profound implications on herd behaviour as studied so far. For example, stock market in Saudi Arabia herd around oil market (Gabbori *et al.*

2021), stock markets in Africa herd around South Africa (Guney *et al.* 2017), and Europe herds around the US market (Chang *et al.* 2020).

It is seems to be apparent that no such relevant benchmark for NASDAQ-100 listed companies exists yet. Therefore, we will use an external factor in a substantionally innovative way. Our portfolio is divided into two subsets based on logic consistent with approach of Chiang & Zheng (2010) who use the US market as a proxy for global market.

First group consists of technological giants as defined by “FAANG”; namely Facebook (Meta Platforms, Inc.), Apple, Amazon, Netflix, Google (Alphabet Inc.). These create an external factor in our case; assumed to be literally a global market due to their long-term domination (Eavis & Lohr 2020; Most stockmarket returns come from a tiny fraction of shares 2018; Wursthorn 2021).

Second group contains remaining 95 listed firms whose impact is—for the purpose of the thesis—restricted within internal market in the USA. This “bouquet” of companies creates primary market in our case, to which we stick if filtering trading sessions based on extreme market volatility or abnormal trading volume.

To secure robustness of the results for various “Big Tech” compositions, specifications regarding technological giants defined by acronyms “FAAG” or “FAAMG” are run as well while deleting Netflix or replacing it by Microsoft.

Following Chang *et al.* (2020), this gives us regression model to be estimated:

$$CSAD_{i,t} = \alpha + \beta_1 |R_{m\_i,t}| + \beta_2 R^2_{m\_i,t} + \gamma_1 CSAD_{j,t} + \gamma_2 R^2_{m\_j,t} + \varepsilon_t \tag{3.15}$$

where the variables $R_{m\_i,t}$ and $R^2_{m\_i,t}$ are related to the primary stock market, while the variables $CSAD_{j,t}$ and $R^2_{m\_j,t}$ stand for the cross-sectional absolute deviation of returns and the squared market return of the external factor j on day t. Specifically, in our case, we denote $i = exclFAANG$ and $j = FAANG$ based on the described NASDAQ-100 index split. Moreover, versions running $i = exclFAAG$ and $j = FAAG$; running $i = exclFAAMG$ and $j = FAAMG$ are considered, too. To point out, dependent variable $CSAD_{i,t}$ is the measure for returns dispersion in the primary market i.

As already mentioned, adding external factor in the model does not prohibit us from simultaneously filtering based on extreme market volatility or extreme trading volume. Therefore, we consider also ensuing specifications regarding high and low market volatility:

$$\begin{aligned} CSAD_{i,t}^{\hat{\sigma}^2,HIGH} &= \alpha + \beta_1^{\hat{\sigma}^2,HIGH}|R_{m\_i,t}^{\hat{\sigma}^2,HIGH}| + \beta_2^{\hat{\sigma}^2,HIGH}(R_{m\_i,t}^{\hat{\sigma}^2,HIGH})^2 \\ &+ \ \gamma_1 CSAD_{j,t} + \gamma_2 R_{m\_j,t}^2 + \varepsilon_t \end{aligned} \tag{3.16}$$

$$\begin{aligned} CSAD_{i,t}^{\hat{\sigma}^2,LOW} &= \alpha + \beta_1^{\hat{\sigma}^2,LOW}|R_{m\_i,t}^{\hat{\sigma}^2,LOW}| + \beta_2^{\hat{\sigma}^2,LOW}(R_{m\_i,t}^{\hat{\sigma}^2,LOW})^2 \\ &+ \ \gamma_1 CSAD_{j,t} + \gamma_2 R_{m\_j,t}^2 + \varepsilon_t \end{aligned} \tag{3.17}$$

where the superscripts $(\hat{\sigma}^2, HIGH)$ and $(\hat{\sigma}^2, LOW)$ refer to high return volatility and low return volatility in the primary market i. Noteworthy, volatility as defined by $\hat{\sigma}^2$ is calculated as the square of the market i portfolio return in period t. To secure robustness of the results, modifications running 7-day, 90-day and 180-day moving averages are considered as well.

Lastly, we cover upgraded versions for extremely high and low trading volume as follows:

$$\begin{aligned} CSAD_{i,t}^{V-HIGH} &= \alpha + \beta_1^{V-HIGH}|R_{m\_i,t}^{V-HIGH}| + \beta_2^{V-HIGH}(R_{m\_i,t}^{V-HIGH})^2 \\ &+ \ \gamma_1 CSAD_{j,t} + \gamma_2 R_{m\_j,t}^2 + \varepsilon_t \end{aligned} \tag{3.18}$$

$$\begin{aligned} CSAD_{i,t}^{V-LOW} &= \alpha + \beta_1^{V-LOW}|R_{m\_i,t}^{V-LOW}| + \beta_2^{V-LOW}(R_{m\_i,t}^{V-LOW})^2 \\ &+ \ \gamma_1 CSAD_{j,t} + \gamma_2 R_{m\_j,t}^2 + \varepsilon_t \end{aligned} \tag{3.19}$$

where the superscripts $(V - HIGH)$ and $(V - LOW)$ refer to high trading volume and low trading volume in the primary market i. To secure robustness of the results, modifications running 7-day, 90-day and 180-day moving averages are considered as well.

Chapter 4

Data

4.1 Dataset

We stick our attention to technology-heavy index NASDAQ-100. It is responsible for about 90% of movements of much wider NASDAQ Composite; the US stock market index which can be ranked among the most important ones in the world. The dataset we construct and employ consists of all 100 firms listed on 30 December 2020 in the already mentioned capitalization-weighted index. In case of Alphabet Inc. and Fox Corporation, both classes of stocks are included which results in 102 tickers in the end. Additionally, the data regarding NASDAQ-100 index itself are considered for simplicity reasons, too. Mainly, we collect daily closing prices adjusted for any corporate actions (splits, dividends etc.) from the publicly available *Yahoo! Finance website*. Moreover, data concerning trading volume are collected as well. Time range starts 3 January 2011 and ends 30 December 2020. Thus, we obtain 2516 daily observations in total.

The portfolio is not adjusted for the annual index rebalancing. As a consequence, stocks delisted during the time period are excluded. Next, some firms went public later than on our starting date of 3 January 2011; even though it still leaves a fairly representative starting grid of 86 tickers. Traded on one of the largest stock exchanges in the world where the stocks are active daily, our models make use of all listed firms in our sample (Chang *et al.* 2000).

4.2 Data processing

Moving forward to the data processing part, the daily stock return is calculated as follows:

$$R_{i,t} = 100 \times [log(P_{i,t}) - log(P_{i,t-1})] \tag{4.1}$$

where $R_{i,t}$ is equal to percentage profit if positive; percentage loss if negative to investor who holds stock i over the day t assuming $P_{i,t}$, respectively $P_{i,t-1}$ denote daily closing prices for given stock i on day t, respectively $t-1$.

As the calculation of both CSSD and CSAD requires derivation of market return, NASDAQ-100 index return is used as a proxy variable. Trading volume concerning whole market is approximated in a similar manner.

For the sake of hypothesis #2, we have to divide our sample into two submarkets. Following popular discussions (Herrman 2019; Most stockmarket returns come from a tiny fraction of shares 2018), companies specified by acronym FAANG represent technological giants and take the vital position of external factor in our case. The rest of the market, that means 95 firms are then said to constitute the primary market. Indeed, two appropriate value-weighted subindices are created; values being the average weight during given time range. Finally, the primary market trading volume is cut by the one of FAANG. As already mentioned, the same procedure is devoted in case of technological giants defined by acronyms FAAG or FAAMG.

In the case of the hypothesis #3, the dataset is restrained to the observations coming from turbulent year of 2020 when both stock market crash and subsequent bull market happened.

Next, we present summary of descriptive statistics regarding final dataset devoted to each tested hypothesis in the Table 4.1. Moreover, the summary

Table 4.1: Descriptive statistics (first-class selection)

Sample	Variable	Mean	Std. d.	Med.	Min	Max	Skewn.	Kurt.	ADF test
Hyp. #1	R_m	0.0691	1.2552	0.1173	-13.0031	9.5966	-0.6811	13.7417	-14.087***
	$CSAD$	1.1268	0.3801	1.0521	0.4151	4.9115	2.7136	18.6687	-7.035***
Hyp. #2	$R_{exclFAANG}$	0.0575	1.2495	0.0872	-13.5754	9.7205	-0.7083	15.1597	-14.100***
	$CSAD_{exclFAANG}$	1.1447	0.5577	1.0444	0	13.2107	8.5884	139.2694	-7.227***
	R_{FAANG}	0.0963	1.4703	0.1418	-11.7932	9.3347	-0.3634	8.2150	-13.965***
	$CSAD_{FAANG}$	0.0565	0.0443	0.0460	0	0.7098	3.8521	33.4408	-9.791***
Hyp. #3	R_{2020}	0.1531	2.3101	0.3762	-13.0032	9.5966	-0.8046	9.4849	-5.595***
	$CSAD_{2020}$	1.5795	0.6503	1.4070	0.7295	4.9115	2.3455	10.1315	-3.509**

of descriptive statistics for remaining Big Tech specifications can be find in the

Appendix A. The same is true for the capturing of skyrocketing technology sector in dependency on the tested hypothesis which is also provided in the Appendix A.

Last but not least, the heteroscedasticity and autocorrelation robust standard errors as suggested by Newey & West (1987) are applied in our regression models to be able to guarantee efficiency of the derived OLS estimators.

Chapter 5

Results and Discussion

5.1 Technology sector

In this section, we provide results of testing the hypothesis #1 concerning “helicopter view”. By this, we mean the examination of the dataset as given to provide a general overview of herding in the technology sector. As a consequence, 100 companies in the index are studied for a maximum of 2516 available trading days. Besides, the “helicopter view” stresses that no economic intuition is used to increase chances of detecting herding by hypotheses specified more in detail.

CSSD regression model

We start with the CSSD methodology proposed by the study of Christie & Huang (1995). At first, we run model following Equation (3.2) using cut-off areas defined by 1% upper tail of market returns and 1% lower tail of market returns. The results are reported in the Table 5.1. The intercept of about 1.672 shows dispersions during average trading day eliminating days considered in extreme tails. Besides, its value can be ranked among the smaller ones compared to the examination provided by Christie & Huang (1995) who also suggests possible explanation of regulated industry for a such small values. Taking into account the reality of technology sector, we could interpret it rather as being created by homogenous firms from the investors’ point of view.

As the estimated coefficient β^L is significant and positive, the stock dispersions in days within 1% of sell-off sessions are significantly higher than during average trading day. Analogically, the significant and positive β^U indicates that dispersions are significantly higher during days within 1% highest returns, too.

Table 5.1: Estimates of herd behaviour within 1% extreme tails

	Dependent variable:
	$CSSD_t$
Constant	1.672^{***}
	(0.028)
D_t^L	1.257^{***}
	(0.369)
D_t^U	1.166^{***}
	(0.273)
Observations	2,515
R^2	0.075
Adjusted R^2	0.074
Residual Std. Error	0.607 (df = 2512)
F Statistic	101.472^{***} (df = 2; 2512)
Note:	*p<0.1; **p<0.05; ***p<0.01

In contrary to the pioneering study of Christie & Huang (1995); we acquire estimates $\beta^L > \beta^U$ which imply that investors tend to differentiate stocks more during largest market downturns than during rather uniform market upswings.

To minimize the effects of potential outlying observations, we also derive linear regression model following Equation (3.2) using 5% criterion instead. The results can be found in the Table 5.2. The key estimated coefficients remain significant and positive, even though their magnitudes decrease. This seems to be fairly logical as we include "less extreme days" into "extreme tails" in comparison to the previous specification. Nevertheless, both obtained results suggest market behaviour in line with standard asset price models, including the one of Sharpe (1964). Thus, we get no evidence of herding in the US stock market given time period 2011-2020 which is in harmony with the study of Christie & Huang (1995) who focus on daily stock prices in the US market from 1962 to 1988.

Table 5.2: Estimates of herd behaviour within 5% extreme tails

	Dependent variable:
	CSSD_t
Constant	1.639^{***}
	(0.025)
D_t^L	0.617^{***}
	(0.132)
D_t^U	0.539^{***}
	(0.111)
Observations	2,515
R^2	0.076
Adjusted R^2	0.075
Residual Std. Error	0.607 (df = 2512)
F Statistic	103.474^{***} (df = 2; 2512)
Note:	*p<0.1; **p<0.05; ***p<0.01

CSAD regression model

Bearing in mind potential drawbacks of the previously utilized approach, let us name for example the "requirement" of disproportionally excessive non-linearity in the relationship to capture herding, we continue using more sophisticated CSAD methodology to secure proper treatment (Chang *et al.* 2000).

We start with the results of our baseline model defined by Equation (3.10) in the Table 5.3. Applying CSAD methodology for the first time, we comment on the underlying core logic more in depth. The constant suggests theoretical stock dispersions for the zero market return session. Specifically, the value of about 0.968 manifests a usual distance of the return dispersion from the market average.

Mainly, the estimated coefficients β_1 and β_2 specify the quadratic functional relationship. The coefficient β_1 related to absolute market return, $|R_{m,t}|$, indicates the slope of the function showing how much individual stock returns deviate from the market benchmark. According to Chang *et al.* (2000), the slopes are dependent on market specific parameters. Most important, the β_2 coefficient linked to the quadratic term, $R^2_{m,t}$, reveals potential non-linearity in the examined relationship. Three outcomes are possible; significant and

Table 5.3: Estimates of herd behaviour, full sample, baseline model

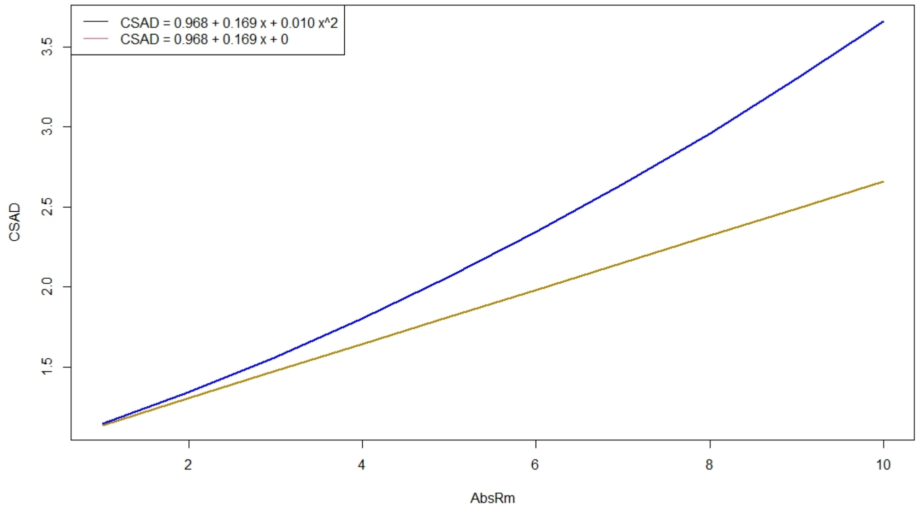
	Dependent variable:
	CSAD_t
Constant	0.968^{***}
	(0.015)
$\lvert \mathrm{R}_{m,t} \rvert$	0.169^{***}
	(0.020)
$\mathrm{R}^2_{m,t}$	0.010^{***}
	(0.002)
Observations	2,515
R^2	0.299
Adjusted R^2	0.298
Residual Std. Error	0.318 (df = 2512)
F Statistic	534.646^{***} (df = 2; 2512)
Note:	*p<0.1; **p<0.05; ***p<0.01

negative, insignificant (regardless whether positive or negative one), and significant and positive one. The first mentioned option, significantly-negative coefficient β_2 is a sign that investors imitate each other sticking to the comfort of market consensus, i.e. participate in herd behaviour. In contrary to that, the insignificant coefficient β_2 suggests verification of the EMH – so that the relationship between CSAD and market return is exactly linear. Finally, the positive and significant coefficient β_2 can be interpreted as violation of EMH in an atypical manner. Indeed, investors are thought to behave in a profoundly individualistic way, their decision-making displays asynchronization and personalisation. Individual stock returns diverge from the market return the more as it increases.

Regarding specifically our results in Table 5.3 stated above, the estimated coefficient of quadratic term, β_2, is positive and significant so that dispersions increase at even increasing rate. According to the given information background, we state that investors decision-making can be described as “too random”, being affected by inevitable uncertainty connected to investing in financial markets, which results in “chaotic” findings on an aggregate level.

The characteristic convexity in the examined relationship which is caused by investors' "too random" choices—compared to a theoretical efficient market—is well illustrated in the Figure 5.1.

Figure 5.1: Technology sector: relationship of $CSAD$ and market return



Source: Author's own computations.

Lastly, our findings are consistent with the methodologically innovative study of Chang *et al.* (2000) who focus on the US market 1963-1997.

CSAD regression model with emphasis on extreme market volatility

Furthermore, to analyse potential asymmetries in herd behaviour, we distinguish trading days with regards to extreme market volatility and extreme trading volume (Economou *et al.* 2011; Tan *et al.* 2008; Tversky & Kahneman 1991). First, the results for the abnormal market volatility—based on pair of Equation (3.11) and Equation (3.12)—are reported in the Table 5.4.

Regarding high volatility, the estimated coefficient of the quadratic term is no longer statistically significant at 5% level. On the contrary, the quadratic term remains positive and significant during low volatile days. For robustness purposes, we report the results for versions using 7-, 90- and 180- day moving averages for both high and low market volatility in the Appendix A. Generally speaking, the choice of the metric does affect results only slighly. Nevertheless, the β_2 related to quadratic term of interest is positive for all moving averages, even though its statistical significance is without warranty.

Table 5.4: Estimates of herding under extreme market volatility based on 30-day moving averages, full sample

	Dependent variable:	
	$CSAD_t$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.831***	0.952***
	(0.041)	(0.022)
$\lvert R_{m,t} \rvert$	0.222***	0.240***
	(0.033)	(0.052)
$R^2_{m,t}$	0.006*	0.030**
	(0.002)	(0.014)
Observations	735	1,751
R^2	0.434	0.190
Adjusted R^2	0.432	0.189
Residual Std. Error	0.348 (df = 732)	0.297 (df = 1748)
F Statistic	280.565*** (df = 2; 732)	204.977*** (df = 2; 1748)
Note:		*p<0.1; **p<0.05; ***p<0.01

CSAD regression model with emphasis on extreme trading volume

Given similar underlying logic, we continue by turning our attention to other set of stressful periods in stock market – filtering days based on extreme trading volume running Equation (3.13); respectively running Equation (3.14). Mainly, the results considering days with volume higher; respectively lower than its 30-day moving average can be found in the Table 5.5.

Table 5.5: Estimates of herding under extreme trading volume based on 30-day moving averages, full sample

	Dependent variable:	
	$CSAD_t$	
	V-HIGH	V-LOW
Constant	1.091***	0.909***
	(0.022)	(0.018)
$\lvert R_{m,t} \rvert$	0.121***	0.142***
	(0.026)	(0.033)
$R^2_{m,t}$	0.013***	0.023***
	(0.002)	(0.008)
Observations	1,096	1,391
R^2	0.293	0.251
Adjusted R^2	0.292	0.250
Residual Std. Error	0.366 (df = 1093)	0.258 (df = 1388)
F Statistic	226.809*** (df = 2; 1093)	232.170*** (df = 2; 1388)
Note:		*p<0.1; **p<0.05; ***p<0.01

Overall, our findings suggest that investors' behaviour is not prone to be affected by different trading volume conditions. Finally, the estimates of the coefficients in both cases seem to be congruous with our up to now findings. The results for the 7-, 90- and 180-day moving averages can be found in the Appendix A.

Discussion #1

To sum up, we find no evidence of herding in the US market with emphasis on the technology sector during period 2011–2020. Results derived by CSSD methodology show increased dispersions during extreme market returns. Moreover, CSAD methodology reveals even remarkable convexity in their increasing rate. The findings differ only slightly if filtering based on abnormal market volatility or trading volume.

5.2 Role of Big Tech

Next, we continue in a more nuanced way by studying the role of the technological giants on the rest of the market. To briefly recall, concerning the hypothesis #2, we relax the assumption of the closed system and add external factor to the regression (Economou *et al.* 2011; Guney *et al.* 2017). To do so, the global FAANG—being excluded from the NASDAQ-100—plays such a crucial role in view of the American exceptionalism (Allen 2014; Chiang & Zheng 2010; Wang 2021). Correspondingly, the primary market now consists of 95 companies assumed to do business mainly on the national level.

CSAD regression model

As already mentioned, the CSSD methodology suffers from number of complicating flaws (Chang *et al.* 2000). Among others, it does not admit external factor in the regression model so we move straightforwardly to the results derived by alternative gradually developed approach (Chang *et al.* 2000; Chiang & Zheng 2010; Economou *et al.* 2011; Tan *et al.* 2008). The results for our baseline model defined by Equation (3.15) are described in the Table 5.6. Adding external factor to the analysis, we will briefly comment on the meaning of the key explanatory variables. Following Chang *et al.* (2020), a negative and statistically significant coefficient β_2 would indicate "domestic" herding towards the primary market. Moreover, a negative and statistically significant coefficient γ_2 would suggest that primary market "externally" herds around the global FAANG. Lastly, a positive and statistically significant coefficient γ_1 would imply that the global FAANG has a dominant influence on the primary market.

Back to the calculated; the estimated coefficients related to the US market remain significant and positive, while coefficient of determination increased. Although dataset moderately differs compared to the hypothesis #1, the very similar estimates could serve us as an indicia of desired unbiasedness of the estimates in the sense of not omitting any relevant variable. Besides, no "domestic" herding in the US market detected.

Moving to the interaction with the global market identified by FAANG, we see that the γ_1 is positive and significant which shows the internal FAANG dispersions are transmitted to the US market. Moreover, with the value of about 1.655, FAANG has an amplifying effect on the US market. This seems to be conceptually in accordance with the comprehensive study of Chiang & Zheng

Table 5.6: Estimates of herd behaviour, global FAANG, baseline model

	Dependent variable:
	$\text{CSAD}_{exclFAANG,t}$
Constant	0.887***
	(0.023)
$\lvert \text{R}_{exclFAANG,t} \rvert$	0.140***
	(0.023)
$\text{R}^2_{exclFAANG,t}$	0.011**
	(0.004)
$\text{CSAD}_{FAANG,t}$	1.655***
	(0.304)
$\text{R}^2_{FAANG,t}$	0.003
	(0.005)
Observations	2,515
R^2	0.346
Adjusted R^2	0.345
Residual Std. Error	0.305 (df = 2510)
F Statistic	331.761*** (df = 4; 2510)
Note:	*p<0.1; **p<0.05; ***p<0.01

(2010) where the "superior" US market is shown to play a vital role in multiple "normal" regional markets. However, the estimated coefficient indicating herding around the FAANG, γ_2, is insignificant. Thus, suggested external factor does not drive herding in the US market. Further, the results for FAAG and FAAMG baseline models are placed in the Appendix A. Similarly to the previous hypothesis, we also specify the model with respect to the extreme market conditions as stated.

CSAD regression model with emphasis on extreme market volatility

At first, days with extreme volatility within the US market, defined as above or below its 30-day moving average are concerned. The results following Equation (3.16), respectively Equation (3.17) in dependence on the turbulency are presented in the Table 5.7.

Table 5.7: Estimates of herding under extreme market volatility based on 30-day moving averages, global FAANG

	Dependent variable:	
	$\text{CSAD}_{exclFAANG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.763***	0.877***
	(0.049)	(0.027)
$\lvert \text{R}_{exclFAANG,t} \rvert$	0.184***	0.199***
	(0.033)	(0.048)
$\text{R}^2_{exclFAANG,t}$	0.006*	0.030**
	(0.003)	(0.015)
$\text{CSAD}_{FAANG,t}$	1.699***	1.647***
	(0.469)	(0.425)
$\text{R}^2_{FAANG,t}$	0.004	0.001
	(0.004)	(0.009)
Observations	744	1,743
R^2	0.496	0.241
Adjusted R^2	0.493	0.240
Residual Std. Error	0.323 (df = 739)	0.289 (df = 1738)
F Statistic	181.828*** (df = 4; 739)	138.335*** (df = 4; 1738)
Note:		*p<0.1; **p<0.05; ***p<0.01

Even the published model with the highest R-squared is in line with the leading argumentation of no herd behaviour detected. However, the barely significant β_2 could imply one possible disruption, while confirming the findings of Kumar *et al.* (2021) of relatively lower β_2 in highly volatile periods. More interestingly, it is suggested efficient-market hypothesis to hold at least for days with high volatility controlling for the effects related to FAANG (Fama 1970). Regarding low volatility, the co-movement of FAANG dispersions and those in the US market is supported, while no evidence of herding around FAANG found. Given positive and significant β_2, we return to the main stream. Lastly, the results for the 7-, 30-, 90- and 180-day moving averages concerning given Big Tech compositions are stored in the Appendix A.

CSAD regression model with emphasis on extreme trading volume

Finally, the results for periods with abnormal trading volume are reported in the Table 5.8 based on the pair of Equation (3.18) and Equation (3.19).

Table 5.8: Estimates of herding under extreme trading volume based on 30-day moving averages, global FAANG

	Dependent variable:	
	$\text{CSAD}_{exclFAANG,t}$	
	V-HIGH	V-LOW
Constant	0.956***	0.857***
	(0.036)	(0.018)
$\lvert \text{R}_{exclFAANG,t} \rvert$	0.105***	0.107***
	(0.030)	(0.027)
$\text{R}^2_{exclFAANG,t}$	0.016***	0.020**
	(0.005)	(0.008)
$\text{CSAD}_{FAANG,t}$	2.252***	1.150***
	(0.534)	(0.196)
$\text{R}^2_{FAANG,t}$	−0.001	0.010**
	(0.008)	(0.004)
Observations	1,139	1,348
R^2	0.374	0.282
Adjusted R^2	0.371	0.279
Residual Std. Error	0.337 (df = 1134)	0.258 (df = 1343)
F Statistic	169.143*** (df = 4; 1134)	131.602*** (df = 4; 1343)
Note:		*p<0.1; **p<0.05; ***p<0.01

Speaking of days with trading volume exceeding 30-day moving average, we get negative estimated coefficient γ_2. However, given its insufficient significance, it would be naïve to use it as an illustration of the US market investors herding around the Big Tech. Regarding “hibernation” periods, the positive and significant γ_2 is worth mentioning. A little boldly, the higher FAANG index return, the higher dispersions in the US market; which shows potentially increased stock selectiveness in case of FAANG surging rally. Moreover, low trading volume can be partially explained by the lack of profitable investment opportunities if FAANG climbs (Langley 2021; Value investing is struggling to remain relevant 2020). Lastly, the results for the 7-, 30-, 90- and 180-day moving averages concerning given Big Tech compositions are stored in the Appendix A.

Discussion #2

To briefly recall, the role of the technological giants in the US stock market is being studied. Most importantly, there is no evidence investors in the US market are prone to herd around the Big Tech indices. On the other hand, the Big Tech dispersions are shown to massively catalyse those in the US market, with the potential risk of destabilising it in the future. It is also argued both specifications—the former with, the latter without external factor—provide reliable estimates of coefficients with regards to the primary market.

5.3 Impact of COVID-19

In our very last hypothesis, hypothesis #3, the dataset is restrained to 252 observations concerning crisis year 2020 which is devoted special treatment (Chang *et al.* 2020; Espinosa-Méndez & Arias 2021; Yarovaya *et al.* 2021). To briefly recall, the panic related to COVID-19 pandemic hit financial markets all around the world from February 2020 to April 2020 (Huang *et al.* 2021). To illustrate the dramatic situation, even technology-heavy NASDAQ-100 plunged by 26% from peak to trough (Huang *et al.* 2021). However, given both the hope of inventing vaccine and the greed of cheap money thanks to macroeconomic stabilization policy, markets recovered very fast. To illustrate, NASDAQ-100 index eventually rise 46% in 2020 regardless the crash earlier that year.

CSSD regression model

The restricted sample is first examined using CSSD methodology as no external factor considered. However, the application of tails defined by 1%, respectively 5% of extreme market returns is not reliable because of relatively small sample. Therefore, we adjust the criteria respecting the "extreme" observations in 2020 detected within the scope of tails as suggested by Christie & Huang (1995) processed on the whole dataset (2011-2020). As a consequence, tails redefined 5%, respectively 12.5% are applied. The results for a "stricter" alternative based on the Equation (3.2) are produced in the Table 5.9.

Table 5.9: Estimates of herd behaviour within 5% extreme tails, year 2020

	Dependent variable:
	CSSD_{2020}
Constant	2.106^{***}
	(0.063)
D^{L}_{2020}	1.451^{***}
	(0.474)
D^{U}_{2020}	1.333^{***}
	(0.357)
Observations	252
R^2	0.227
Adjusted R^2	0.221
Residual Std. Error	0.787 (df = 249)
F Statistic	36.557^{***} (df = 2; 249)
Note:	*p<0.1; **p<0.05; ***p<0.01

In comparison to the "stricter" modification concerning whole decade, the intercept of 2.106 is considerably bigger than the one of 1.672 which expresses that "pandemic average" is more chaotic than the "normal average".

Most important, as the estimated coefficients β^L and β^U remain statistically significant and even increase, we get indicia of either "substantively" more stressful market period itself or "only" more chaotic investors decision-making. Nevertheless, no evidence of herding is obtained for the 5% extreme tails in 2020.

We continue by "loosening" our tails following Equation (3.2); lower one to 12.5% and upper one to 12.5% observations too. The results are displayed in the Table 5.10.

What we obtain appears to be in line with overall picture as given by approach suggested by the study of Christie & Huang (1995). The estimated coefficients are smaller than for the "stricter" version of 2020; even though greatly bigger than for corresponding model concerning maximum time range

Table 5.10: Estimates of herd behaviour within 12.5% extreme tails, year 2020

	Dependent variable:
	$CSSD_{2020}$
Constant	2.056***
	(0.068)
D^L_{2020}	0.811***
	(0.296)
D^U_{2020}	0.720***
	(0.212)
Observations	252
R^2	0.141
Adjusted R^2	0.134
Residual Std. Error	0.830 (df = 249)
F Statistic	20.416*** (df = 2; 249)
Note:	*p<0.1; **p<0.05; ***p<0.01

available. Besides, the relationship of $\beta^L > \beta^U$ remains intact as well. Nonetheless, no evidence of herding earned

CSAD regression model

Next, we continue by presenting and discussing results derived by approach suggested by the pioneering study of Chang *et al.* (2000). Following Equation (3.10), the summary of the results for our "pandemic" baseline model is offered in the Table 5.11.

As shown above, the constant noticeable increases compared with the estimate reflecting period 2011–2020. Nevertheless, the value of about 1.288 falls within the norm as well. To continue, the β_1 remains positive and significant in the similar manner. Most crucial, the β_2 is still positive but not further statistically significant at even 5% level. Therefore, the convexity in the examined relationship of dispersion and market return still exists but is no longer dominant marker here. Given "chaotic" findings concerning whole decade, the space for trickier interpretation emerges – assuming rather "chaotic background compensated by herding episodes" than "inherent efficiency" with

Table 5.11: Estimates of herd behaviour, year 2020, baseline model

	Dependent variable:
	$CSAD_{2020}$
Constant	1.288^{***}
	(0.054)
$\lvert R_{m,2020} \rvert$	0.161^{***}
	(0.060)
$R^2_{m,2020}$	0.008^{*}
	(0.004)
Observations	252
R^2	0.370
Adjusted R^2	0.365
Residual Std. Error	0.518 (df = 249)
F Statistic	73.071^{***} (df = 2; 249)
Note:	*p<0.1; **p<0.05; ***p<0.01

regards to verification of the EMH. Finally, the days with regards to extreme market conditions are devoted special treatment to complete our analysis.

CSAD regression model with emphasis on extreme market volatility

Running pair of Equation (3.11) and Equation (3.12). we examine days with respect to the market volatility. Unfortunately, we cannot straightforwardly determine if the volatility is related to the stock market crash or to the—similarly outpacing—bull market. Nevertheless, we report the resuls in the Table 5.12.

Regarding unexpected pandemic, we acquire also relatively unexpected results. In case of highly volatile periods, both derived estimated coefficients remain positive but not statistically significant even at 5% level. Besides, the R-squared is surprisingly high. Commenting on low volatility, β_1 and β_2 seems to be confusing and challenging to interpret at first. Given low coefficient of determination, possible explanation lies in the point that quadratic term probably "steals" some part of the upward trend from the linear term. The results for the 7-, 90- and 180-day moving averages can be found in the Appendix A.

Table 5.12: Estimates of herding under extreme market volatility based on 30-day moving averages, year 2020

	Dependent variable:	
	$CSAD_{2020}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	1.273***	1.441***
	(0.292)	(0.074)
$\lvert R_{m,2020} \rvert$	0.145	−0.038
	(0.129)	(0.105)
$R^2_{m,2020}$	0.010	0.067***
	(0.008)	(0.024)
Observations	64	159
R^2	0.491	0.165
Adjusted R^2	0.474	0.155
Residual Std. Error	0.605 (df = 61)	0.503 (df = 156)
F Statistic	29.432*** (df = 2; 61)	15.468*** (df = 2; 156)
Note:		*p<0.1; **p<0.05; ***p<0.01

CSAD regression model with emphasis on extreme trading volume

To complete testing hypothesis #3, the results concerning abnormal trading volume are presented running both Equation (3.13) and Equation (3.14). Mainly, the results are announced in the Table 5.13.

Table 5.13: Estimates of herding under extreme trading volume based on 30-day moving averages, year 2020

	Dependent variable:	
	$CSAD_{2020}$	
	V-HIGH	V-LOW
Constant	1.545^{***}	1.303^{***}
	(0.078)	(0.072)
$\lvert R_{m,2020} \rvert$	0.119	0.062
	(0.093)	(0.071)
$R^2_{m,2020}$	0.010	0.024^{**}
	(0.007)	(0.011)
Observations	90	133
R^2	0.341	0.282
Adjusted R^2	0.326	0.271
Residual Std. Error	0.703 (df = 87)	0.354 (df = 130)
F Statistic	22.532^{***} (df = 2; 87)	25.510^{***} (df = 2; 130)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

It is acknowledged that even trading volume does not provide us with the relevant guidance in finding any special pattern in investors behaviour during year 2020 full of dramatic shifts. Last but not least, the results for the 7-, 90- and 180-day moving averages can be found in the Appendix A.

Discussion #3

To sum up, the year 2020 can be regarded as extremely useful to study investors behaviour under stressful periods. Firstly, the dispersions remarkably increase in general compared to whole decade. Although regression models themselves indicate that efficient-market hypothesis holds, our conclusion—based on deeper analysis—suggests that investors—very likely—exhibit herding during both stock market crash and subsequent bull market. In addition, we observe less convexity in the examined relationship.

5.4 Evaluation of research hypotheses

[#1] There is no statistically significant herd behaviour in the technology sector (as a helicopter view)

Generally supported *Noteworthy, neither efficient-market hypothesis holds as investors are surprisingly shown to pick stocks in an excessively individualistic style.*

[#2] Technology giants have no statistically significant association to herd behaviour in the rest of the technology sector

Cannot say *Although no herd behaviour detected, the remarkable contagion from the Big Tech to the rest of the US market indicate a close interconnection.*

[#3] Herd behaviour played no statistically significant role in both 2020 stock market crash and subsequent bull market

Partially rejected *Following less convexity in the examined relationship, it is thought that individualistic background is redeemed by herding episodes during the crisis.*

Chapter 6

Conclusion

This thesis focuses on studying the prevalence of herd behaviour in financial markets with emphasis on the technology sector. To do so, commonly used CSAD methodology—based on the measure of cross-sectional absolute deviation of returns—and CSSD methodology—based on the measure of cross-sectional standard deviation of returns—are considered (Chang *et al.* 2000; Christie & Huang 1995; Economou *et al.* 2011; Tan *et al.* 2008). In addition, the dataset we construct and employ consists of all 100 firms listed in technology-heavy index NASDAQ-100 and deals with time period 2011–2020.

Firstly, the technology sector as a whole is analysed to provide a starting helicopter view. Studying the sample as given, we find literally no evidence of herd behaviour. However, we cannot conclude that stock market would exhibit efficiency as investors are shown to pick stocks in excessively individualistic style. Given "too random" choices, the examined relationship suffers from prolonged convexity which violates traditional finance assumptions (Fama 1970; Black 1972). Besides, results vary only slightly if filtering trading sessions according to extreme market volatility or abnormal trading volume.

Although herd behaviour is a wonderful example of disturbed cognitive patterns, "errors", called cognitive biases (Bikhchandani & Sharma 2000; Bondt *et al.* 2015; Tversky & Kahneman 1974); it is demonstrated how challenging its detection in practice may be. Indeed, our findings are in harmony with those provided by pioneering studies which show no evidence of herding across various industries and indices mapping the US market 1925-1997 (Chang *et al.* 2000; Christie & Huang 1995). However, we have to be aware of changing nature of trading and investing in financial markets – which is no longer a distinctly human affair but large amount of trades is processed automatically using sophisticated artificial intelligence (The stockmarket is now run by computers, algorithms and passive managers 2019). Nevertheless, even the comprehensive study of Chiang & Zheng (2010) suggests that difficulty of revealing herding in the US market remains high.

Shifting to the hypothesis #2, we introduce a novel feature extending the usage of an external factor. As shown, it can be used to study both intra-market contagion and intra-market herding based on market-specific characteristics. In our case, the largest publicly traded companies in the world—Big Tech—with the influence beyond the scope of mere technological innovation take a lead (Eavis & Lohr 2020; Most stockmarket returns come from a tiny fraction of shares 2018; Wursthorn 2021). We find remarkable co-movement of the Big Tech dispersion and those related to the rest of the technology sector. However, given the experimental nature, it is acknowledged that part of the investors does not reflect Big Tech dominant position in their decision-making. Therefore, we cannot decide whether we really find existing contagion or "only" spurious one. Besides, no herding detected even when running this specification.

Indeed, we cannot ignore that a surging rally can be at least partially explained thanks to fundamental variables. Most important, rising revenues and profit margins in the field—compared to markets in Europe or other sectors in the US market—justify attractiveness in the eyes of investors (Lee & Graffeo 2021).

In our very last hypothesis, hypothesis #3, the dataset is restrained to the observations coming from the "viral" year 2020 when COVID-19 pandemic hit world financial markets (Huang *et al.* 2021). The aim here is to find out whether the unexpected and sudden major crisis affects investors behaviour. Sticking merely to the results derived while testing this hypothesis, we would probably conclude that no herding detected and would probably verify the efficient-market hypothesis. However; remembering "too random" findings related to the hypothesis #1 for maximal available time range 2011–2020, we have to be really careful while giving rise to a trickier interpretation. As the convexity in the examined relationship is no longer a key marker here, it is thought that both stock market crash and subsequent bull market were affected—amplified—by herding episodes.

Although our results are not indicative of an inflating bubble in the technology sector, investors should consider expected tightening of monetary policy by the Federal Reserve in the USA and other central banks all around the world. In fact, Fed is hinting that it will raise interest rates three times in

2022 to combat "permanently temporary" inflation (Lee 2021). This is of concerns especially in the case of companies in technology sector as the earnings discounted in the distant future will no longer be so profitable.

It is desirable to note that further research may feel free to continue in a more creative application of external factor based on intuitively perceived market-specific characteristics. Given the potential here, this would reveal—until now hidden—interaction patterns within one market which are as important as the cross-border ones to consider when one is investing. Regarding the US market, running similar analysis with emphasis on "blue-chip" S&P 500 index or "small-cap" Russell 2000 index would increase validity of presented paper. The same applies to examining the technology sector in various Asian countries, where also political factors need to be taken into account.

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Appendix A

Appended Tables and Figures

Appended tables

Descriptive statistics

Table A.1: Descriptive statistics (business class selection)

Sample	| Variable	Mean	Std. d.	Med.	Min	Max	Skewn.	Kurt.	ADF test
Hyp. #2b	$R_{exclFAAG}$	0.0586	1.2501	0.0906	-13.5457	9.6658	-0.7211	14.9961	-14.111***
	$CSAD_{exclFAAG}$	1.1514	0.5544	1.0516	0	13.0767	8.4804	136.7131	-7.204***
	R_{FAAG}	0.0956	1.4728	0.1481	-11.7925	9.4423	-0.3322	8.3044	-14.006***
	$CSAD_{FAAG}$	0.0326	0.0312	0.0267	-0.0649	0.3542	2.6604	16.7385	-10.227***
Hyp. #2c	$R_{exclFAAMG}$	0.0534	1.2447	0.0901	-13.1764	9.1075	-0.7400	14.2287	-14.069***
	$CSAD_{exclFAAMG}$	1.1664	0.5546	1.0667	0.4187	13.1826	8.5367	138.9882	-7.250***
	R_{FAAMG}	0.0946	1.4145	0.1483	-12.7449	10.3253	-0.3844	10.2820	-13.985***
	$CSAD_{FAAMG}$	0.0461	0.0357	0.0375	0	0.4021	3.2079	19.7155	-9.919***

Hypothesis #1

Table A.2: Estimates of herding under extreme market conditions based on 7-day moving averages, full sample

	Dependent variable:	
	CSAD$_t$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.873***	0.957***
	(0.032)	(0.022)
$\|R_{m,t}\|$	0.197***	0.240***
	(0.026)	(0.056)
$R^2_{m,t}$	0.007***	0.031***
	(0.003)	(0.011)
Observations	852	1,657
R^2	0.440	0.216
Adjusted R^2	0.439	0.215
Residual Std. Error	0.320 (df = 849)	0.306 (df = 1654)
F Statistic	333.955*** (df = 2; 849)	228.051*** (df = 2; 1654)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	CSAD$_t$	
	V-HIGH	V-LOW
Constant	1.033***	0.925***
	(0.024)	(0.016)
$\|R_{m,t}\|$	0.176***	0.156***
	(0.032)	(0.025)
$R^2_{m,t}$	0.003	0.015***
	(0.004)	(0.002)
Observations	1,120	1,390
R^2	0.219	0.369
Adjusted R^2	0.218	0.369
Residual Std. Error	0.362 (df = 1117)	0.268 (df = 1387)
F Statistic	157.056*** (df = 2; 1117)	406.332*** (df = 2; 1387)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.3: Estimates of herding under extreme market conditions based on 90-day moving averages, full sample

	Dependent variable: CSAD$_t$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.811***	0.948***
	(0.055)	(0.020)
$\lvert R_{m,t}\rvert$	0.231***	0.227***
	(0.040)	(0.062)
$R^2_{m,t}$	0.005*	0.036*
	(0.003)	(0.031)
Observations	659	1,767
R^2	0.456	0.134
Adjusted R^2	0.454	0.133
Residual Std. Error	0.355 (df = 656)	0.291 (df = 1764)
F Statistic	275.033*** (df = 2; 656)	136.438*** (df = 2; 1764)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable: CSAD$_t$	
	V-HIGH	V-LOW
Constant	1.096***	0.909***
	(0.025)	(0.014)
$\lvert R_{m,t}\rvert$	0.114***	0.140***
	(0.029)	(0.029)
$R^2_{m,t}$	0.014***	0.022***
	(0.003)	(0.007)
Observations	1,033	1,394
R^2	0.310	0.206
Adjusted R^2	0.309	0.205
Residual Std. Error	0.361 (df = 1030)	0.254 (df = 1391)
F Statistic	231.758*** (df = 2; 1030)	180.370*** (df = 2; 1391)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.4: Estimates of herding under extreme market conditions based on 180-day moving averages, full sample

	Dependent variable: CSAD$_t$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.831***	0.966***
	(0.060)	(0.020)
$\lvert R_{m,t}\rvert$	0.220***	0.109**
	(0.043)	(0.053)
$R^2_{m,t}$	0.006*	0.120***
	(0.003)	(0.043)
Observations	609	1,727
R^2	0.444	0.128
Adjusted R^2	0.442	0.127
Residual Std. Error	0.363 (df = 606)	0.290 (df = 1724)
F Statistic	242.116*** (df = 2; 606)	126.015*** (df = 2; 1724)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable: CSAD$_t$	
	V-HIGH	V-LOW
Constant	1.110***	0.909***
	(0.026)	(0.017)
$\lvert R_{m,t}\rvert$	0.110***	0.111***
	(0.029)	(0.030)
$R^2_{m,t}$	0.015***	0.028**
	(0.003)	(0.011)
Observations	1,013	1,324
R^2	0.304	0.134
Adjusted R^2	0.303	0.132
Residual Std. Error	0.371 (df = 1010)	0.237 (df = 1321)
F Statistic	220.697*** (df = 2; 1010)	101.923*** (df = 2; 1321)
Note:		*p<0.1; **p<0.05; ***p<0.01

Hypothesis #2

Table A.5: Estimates of herd behaviour, global FAAG, baseline model

	Dependent variable:
	$CSAD_{exclFAAG,t}$
Constant	0.897***
	(0.022)
$\lvert R_{exclFAAG,t} \rvert$	0.144***
	(0.024)
$R^2_{exclFAAG,t}$	0.010***
	(0.004)
$CSAD_{FAAG,t}$	2.293***
	(0.371)
$R^2_{FAAG,t}$	0.003
	(0.005)
Observations	2,515
R^2	0.343
Adjusted R^2	0.342
Residual Std. Error	0.306 (df = 2510)
F Statistic	328.141*** (df = 4; 2510)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.6: Estimates of herd behaviour, global FAAMG, baseline model

	Dependent variable:
	$CSAD_{exclFAAMG,t}$
Constant	0.889***
	(0.023)
$\lvert R_{exclFAAMG,t} \rvert$	0.145***
	(0.022)
$R^2_{exclFAAMG,t}$	0.009*
	(0.005)
$CSAD_{FAAMG,t}$	2.164***
	(0.330)
$R^2_{FAAMG,t}$	0.004
	(0.005)
Observations	2,515
R^2	0.340
Adjusted R^2	0.339
Residual Std. Error	0.307 (df = 2510)
F Statistic	323.758*** (df = 4; 2510)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.7: Estimates of herding under extreme market conditions based on 7-day moving averages, global FAANG

	Dependent variable:	
	$CSAD_{exclFAANG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.812***	0.875***
	(0.034)	(0.031)
$\lvert R_{exclFAANG,t}\rvert$	0.166***	0.198**
	(0.024)	(0.061)
$R^2_{exclFAANG,t}$	0.005	0.034***
	(0.003)	(0.007)
$CSAD_{FAANG,t}$	1.361***	1.743***
	(0.297)	(0.416)
$R^2_{FAANG,t}$	0.006*	0.003
	(0.003)	(0.008)
Observations	854	1,656
R^2	0.503	0.267
Adjusted R^2	0.501	0.266
Residual Std. Error	0.296 (df = 849)	0.297 (df = 1651)
F Statistic	214.979*** (df = 4; 849)	150.665*** (df = 4; 1651)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$CSAD_{exclFAANG,t}$	
	V-HIGH	V-LOW
Constant	0.940***	0.851***
	(0.031)	(0.023)
$\lvert R_{exclFAANG,t}\rvert$	0.133***	0.136***
	(0.030)	(0.027)
$R^2_{exclFAANG,t}$	0.009	0.011***
	(0.007)	(0.004)
$CSAD_{FAANG,t}$	1.981***	1.332***
	(0.416)	(0.264)
$R^2_{FAANG,t}$	0.001	0.005*
	(0.008)	(0.005)
Observations	1,169	1,341
R^2	0.277	0.419
Adjusted R^2	0.275	0.417
Residual Std. Error	0.337 (df = 1164)	0.262 (df = 1336)
F Statistic	111.623*** (df = 4; 1164)	240.965*** (df = 4; 1336)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.8: Estimates of herding under extreme market conditions based on 7-day moving averages, global FAAG

	Dependent variable:	
	$CSAD_{exclFAAG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.821***	0.888***
	(0.035)	(0.028)
$\lvert R_{exclFAAG,t}\rvert$	0.165***	0.215***
	(0.025)	(0.063)
$R^2_{exclFAAG,t}$	0.004	0.031***
	(0.003)	(0.007)
$CSAD_{FAAG,t}$	2.090***	2.289***
	(0.370)	(0.534)
$R^2_{FAAG,t}$	0.007**	0.001
	(0.003)	(0.007)
Observations	861	1,649
R^2	0.500	0.265
Adjusted R^2	0.498	0.264
Residual Std. Error	0.295 (df = 856)	0.300 (df = 1644)
F Statistic	214.421*** (df = 4; 856)	148.468*** (df = 4; 1644)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$CSAD_{exclFAAG,t}$	
	V-HIGH	V-LOW
Constant	0.958***	0.859***
	(0.029)	(0.020)
$\lvert R_{exclFAAG,t}\rvert$	0.140***	0.139***
	(0.030)	(0.026)
$R^2_{exclFAAG,t}$	0.009	0.009***
	(0.007)	(0.004)
$CSAD_{FAAG,t}$	2.551***	1.903***
	(0.550)	(0.333)
$R^2_{FAAG,t}$	−0.0001	0.007**
	(0.008)	(0.004)
Observations	1,170	1,340
R^2	0.278	0.412
Adjusted R^2	0.276	0.410
Residual Std. Error	0.338 (df = 1165)	0.265 (df = 1335)
F Statistic	112.202*** (df = 4; 1165)	233.745*** (df = 4; 1335)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.9: Estimates of herding under extreme market conditions based on 7-day moving averages, global FAAMG

	Dependent variable:			*Dependent variable:*	
	$CSAD_{exclFAAMG,t}$			$CSAD_{exclFAAMG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW		V-HIGH	V-LOW
Constant	0.831^{***}	0.878^{***}	Constant	0.948^{***}	0.851^{***}
	(0.035)	(0.031)		(0.029)	(0.024)
$\lvert R_{exclFAAMG,t}\rvert$	0.163^{***}	0.198^{***}	$\lvert R_{exclFAAMG,t}\rvert$	0.145^{***}	0.140^{***}
	(0.025)	(0.067)		(0.029)	(0.031)
$R^2_{exclFAAMG,t}$	0.003	0.033^{***}	$R^2_{exclFAAMG,t}$	0.007	0.010^{***}
	(0.004)	(0.006)		(0.008)	(0.005)
$CSAD_{FAAMG,t}$	1.879^{***}	2.240^{***}	$CSAD_{FAAMG,t}$	2.291^{***}	1.922^{***}
	(0.338)	(0.485)		(0.457)	(0.318)
$R^2_{FAAMG,t}$	0.007^{**}	0.002	$R^2_{FAAMG,t}$	0.002	0.005
	(0.003)	(0.010)		(0.008)	(0.005)
Observations	859	1,651	Observations	1,179	1,331
R^2	0.476	0.266	R^2	0.276	0.407
Adjusted R^2	0.473	0.264	Adjusted R^2	0.274	0.405
Residual Std. Error	0.302 (df = 854)	0.299 (df = 1646)	Residual Std. Error	0.338 (df = 1174)	0.266 (df = 1326)
F Statistic	193.705^{***} (df = 4; 854)	149.264^{***} (df = 4; 1646)	F Statistic	112.056^{***} (df = 4; 1174)	227.369^{***} (df = 4; 1326)
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

Table A.10: Estimates of herding under extreme market conditions based on 30-day moving averages, global FAAG

	Dependent variable:			*Dependent variable:*	
	$CSAD_{exclFAAG,t}$			$CSAD_{exclFAAG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW		V-HIGH	V-LOW
Constant	0.755^{***}	0.884^{***}	Constant	0.983^{***}	0.857^{***}
	(0.047)	(0.026)		(0.031)	(0.018)
$\lvert R_{exclFAAG,t}\rvert$	0.191^{***}	0.224^{***}	$\lvert R_{exclFAAG,t}\rvert$	0.110^{***}	0.121^{***}
	(0.034)	(0.049)		(0.032)	(0.026)
$R^2_{exclFAAG,t}$	0.005	0.026^{***}	$R^2_{exclFAAG,t}$	0.015^{***}	0.018^{***}
	(0.003)	(0.015)		(0.005)	(0.007)
$CSAD_{FAAG,t}$	2.607^{***}	2.298^{***}	$CSAD_{FAAG,t}$	2.604^{***}	1.801^{***}
	(0.515)	(0.566)		(0.576)	(0.310)
$R^2_{FAAG,t}$	0.004	-0.001	$R^2_{FAAG,t}$	-0.001	0.009^{***}
	(0.003)	(0.009)		(0.008)	(0.004)
Observations	747	1,740	Observations	1,140	1,347
R^2	0.503	0.238	R^2	0.364	0.283
Adjusted R^2	0.500	0.236	Adjusted R^2	0.362	0.281
Residual Std. Error	0.320 (df = 742)	0.291 (df = 1735)	Residual Std. Error	0.340 (df = 1135)	0.261 (df = 1342)
F Statistic	187.647^{***} (df = 4; 742)	135.286^{***} (df = 4; 1735)	F Statistic	162.472^{***} (df = 4; 1135)	132.521^{***} (df = 4; 1342)
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

Table A.11: Estimates of herding under extreme market conditions based on 30-day moving averages, global FAAMG

	Dependent variable:	
	$CSAD_{exclFAAMG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.735***	0.873***
	(0.060)	(0.027)
$\lvert R_{exclFAAMG,t} \rvert$	0.204***	0.252***
	(0.039)	(0.053)
$R^2_{exclFAAMG,t}$	0.005	0.002
	(0.005)	(0.015)
$CSAD_{FAAMG,t}$	2.504***	1.995***
	(0.490)	(0.413)
$R^2_{FAAMG,t}$	0.003	0.004
	(0.005)	(0.007)
Observations	735	1,752
R^2	0.488	0.208
Adjusted R^2	0.486	0.206
Residual Std. Error	0.335 (df = 730)	0.288 (df = 1747)
F Statistic	174.178*** (df = 4; 730)	114.407*** (df = 4; 1747)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$CSAD_{exclFAAMG,t}$	
	V-HIGH	V-LOW
Constant	0.972***	0.851***
	(0.031)	(0.024)
$\lvert R_{exclFAAMG,t} \rvert$	0.112***	0.120***
	(0.028)	(0.030)
$R^2_{exclFAAMG,t}$	0.013**	0.016**
	(0.005)	(0.007)
$CSAD_{FAAMG,t}$	2.393***	1.823***
	(0.508)	(0.338)
$R^2_{FAAMG,t}$	0.001	0.010**
	(0.006)	(0.006)
Observations	1,143	1,344
R^2	0.361	0.280
Adjusted R^2	0.359	0.278
Residual Std. Error	0.339 (df = 1138)	0.264 (df = 1339)
F Statistic	160.890*** (df = 4; 1138)	130.373*** (df = 4; 1339)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.12: Estimates of herding under extreme market conditions based on 90-day moving averages, global FAANG

	Dependent variable:	
	$CSAD_{exclFAANG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.716***	0.887***
	(0.076)	(0.021)
$\lvert R_{exclFAANG,t} \rvert$	0.205***	0.155***
	(0.050)	(0.048)
$R^2_{exclFAANG,t}$	0.008*	0.056***
	(0.004)	(0.029)
$CSAD_{FAANG,t}$	1.852***	1.387***
	(0.411)	(0.277)
$R^2_{FAANG,t}$	0.0002	0.009**
	(0.007)	(0.005)
Observations	649	1,778
R^2	0.538	0.187
Adjusted R^2	0.536	0.185
Residual Std. Error	0.324 (df = 644)	0.283 (df = 1773)
F Statistic	187.780*** (df = 4; 644)	101.847*** (df = 4; 1773)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$CSAD_{exclFAANG,t}$	
	V-HIGH	V-LOW
Constant	0.962***	0.851***
	(0.041)	(0.019)
$\lvert R_{exclFAANG,t} \rvert$	0.097***	0.104***
	(0.034)	(0.030)
$R^2_{exclFAANG,t}$	0.014***	0.026***
	(0.005)	(0.007)
$CSAD_{FAANG,t}$	2.233***	1.293***
	(0.577)	(0.192)
$R^2_{FAANG,t}$	0.002	0.002
	(0.008)	(0.004)
Observations	1,076	1,351
R^2	0.387	0.250
Adjusted R^2	0.385	0.248
Residual Std. Error	0.336 (df = 1071)	0.248 (df = 1346)
F Statistic	169.000*** (df = 4; 1071)	112.436*** (df = 4; 1346)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.13: Estimates of herding under extreme market conditions based on 90-day moving averages, global FAAG

	Dependent variable:	
	$\mathrm{CSAD}_{exclFAAG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.721***	0.889***
	(0.074)	(0.022)
$\lvert \mathrm{R}_{exclFAAG,t} \rvert$	0.213***	0.182***
	(0.048)	(0.055)
$\mathrm{R}^2_{exclFAAG,t}$	0.007*	0.048**
	(0.004)	(0.031)
$\mathrm{CSAD}_{FAAG,t}$	2.400***	2.034***
	(0.528)	(0.380)
$\mathrm{R}^2_{FAAG,t}$	0.001	0.007*
	(0.007)	(0.005)
Observations	650	1,777
R^2	0.542	0.188
Adjusted R^2	0.539	0.186
Residual Std. Error	0.321 (df = 645)	0.285 (df = 1772)
F Statistic	190.474*** (df = 4; 645)	102.733*** (df = 4; 1772)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$\mathrm{CSAD}_{exclFAAG,t}$	
	V-HIGH	V-LOW
Constant	0.991***	0.854***
	(0.035)	(0.020)
$\lvert \mathrm{R}_{exclFAAG,t} \rvert$	0.100***	0.118***
	(0.035)	(0.030)
$\mathrm{R}^2_{exclFAAG,t}$	0.014***	0.024***
	(0.004)	(0.007)
$\mathrm{CSAD}_{FAAG,t}$	2.658***	1.906***
	(0.637)	(0.298)
$\mathrm{R}^2_{FAAG,t}$	0.002	0.002
	(0.008)	(0.003)
Observations	1,069	1,358
R^2	0.378	0.254
Adjusted R^2	0.376	0.252
Residual Std. Error	0.339 (df = 1064)	0.251 (df = 1353)
F Statistic	161.652*** (df = 4; 1064)	115.067*** (df = 4; 1353)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.14: Estimates of herding under extreme market conditions based on 90-day moving averages, global FAAMG

	Dependent variable:	
	$\mathrm{CSAD}_{exclFAAMG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.721***	0.887***
	(0.071)	(0.024)
$\lvert \mathrm{R}_{exclFAAMG,t} \rvert$	0.209***	0.153***
	(0.043)	(0.065)
$\mathrm{R}^2_{exclFAAMG,t}$	0.007	0.067***
	(0.006)	(0.043)
$\mathrm{CSAD}_{FAAMG,t}$	2.277***	1.912***
	(0.526)	(0.337)
$\mathrm{R}^2_{FAAMG,t}$	0.0005	0.010**
	(0.006)	(0.006)
Observations	653	1,774
R^2	0.537	0.189
Adjusted R^2	0.534	0.188
Residual Std. Error	0.320 (df = 648)	0.286 (df = 1769)
F Statistic	187.714*** (df = 4; 648)	103.380*** (df = 4; 1769)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$\mathrm{CSAD}_{exclFAAMG,t}$	
	V-HIGH	V-LOW
Constant	0.975***	0.849***
	(0.036)	(0.020)
$\lvert \mathrm{R}_{exclFAAMG,t} \rvert$	0.102***	0.113***
	(0.033)	(0.028)
$\mathrm{R}^2_{exclFAAMG,t}$	0.012**	0.027***
	(0.005)	(0.007)
$\mathrm{CSAD}_{FAAMG,t}$	2.581***	1.825***
	(0.560)	(0.287)
$\mathrm{R}^2_{FAAMG,t}$	0.003	0.0001
	(0.006)	(0.004)
Observations	1,080	1,347
R^2	0.375	0.255
Adjusted R^2	0.373	0.253
Residual Std. Error	0.338 (df = 1075)	0.251 (df = 1342)
F Statistic	161.246*** (df = 4; 1075)	115.092*** (df = 4; 1342)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.15: Estimates of herding under extreme market conditions based on 180-day moving averages, global FAANG

	Dependent variable:	
	$CSAD_{exclFAANG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.713***	0.913***
	(0.087)	(0.022)
$\lvert R_{exclFAANG,t} \rvert$	0.199***	−0.008
	(0.055)	(0.060)
$R^2_{exclFAANG,t}$	0.008*	0.178***
	(0.005)	(0.049)
$CSAD_{FAANG,t}$	2.114***	1.408***
	(0.439)	(0.299)
$R^2_{FAANG,t}$	0.001	0.008**
	(0.008)	(0.005)
Observations	592	1,745
R^2	0.532	0.178
Adjusted R^2	0.529	0.176
Residual Std. Error	0.334 (df = 587)	0.280 (df = 1740)
F Statistic	166.793*** (df = 4; 587)	94.403*** (df = 4; 1740)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$CSAD_{exclFAANG,t}$	
	V-HIGH	V-LOW
Constant	0.981***	0.836***
	(0.046)	(0.017)
$\lvert R_{exclFAANG,t} \rvert$	0.090**	0.113***
	(0.036)	(0.034)
$R^2_{exclFAANG,t}$	0.016***	0.022*
	(0.005)	(0.012)
$CSAD_{FAANG,t}$	2.210***	1.284***
	(0.636)	(0.200)
$R^2_{FAANG,t}$	0.001	0.003
	(0.008)	(0.005)
Observations	1,048	1,289
R^2	0.383	0.209
Adjusted R^2	0.381	0.206
Residual Std. Error	0.342 (df = 1043)	0.236 (df = 1284)
F Statistic	161.854*** (df = 4; 1043)	84.614*** (df = 4; 1284)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.16: Estimates of herding under extreme market conditions based on 180-day moving averages, global FAAG

	Dependent variable:	
	$CSAD_{exclFAAG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW
Constant	0.720***	0.915***
	(0.082)	(0.021)
$\lvert R_{exclFAAG,t} \rvert$	0.209***	0.025
	(0.052)	(0.060)
$R^2_{exclFAAG,t}$	0.006	0.168***
	(0.004)	(0.050)
$CSAD_{FAAG,t}$	2.652***	2.027***
	(0.575)	(0.376)
$R^2_{FAAG,t}$	0.002	0.005
	(0.007)	(0.005)
Observations	603	1,734
R^2	0.532	0.180
Adjusted R^2	0.529	0.178
Residual Std. Error	0.331 (df = 598)	0.282 (df = 1729)
F Statistic	169.885*** (df = 4; 598)	95.042*** (df = 4; 1729)
Note:		*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$CSAD_{exclFAAG,t}$	
	V-HIGH	V-LOW
Constant	1.015***	0.849***
	(0.036)	(0.019)
$\lvert R_{exclFAAG,t} \rvert$	0.093***	0.095***
	(0.036)	(0.034)
$R^2_{exclFAAG,t}$	0.015***	0.032**
	(0.004)	(0.015)
$CSAD_{FAANG,t}$	2.498***	1.833***
	(0.614)	(0.290)
$R^2_{FAANG,t}$	0.002	0.004
	(0.007)	(0.004)
Observations	1,045	1,292
R^2	0.374	0.201
Adjusted R^2	0.371	0.198
Residual Std. Error	0.345 (df = 1040)	0.237 (df = 1287)
F Statistic	155.009*** (df = 4; 1040)	80.832*** (df = 4; 1287)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.17: Estimates of herding under extreme market conditions based on 180-day moving averages, global FAAMG

	Dependent variable:			*Dependent variable:*	
	$CSAD_{exclFAAMG,t}$			$CSAD_{exclFAAMG,t}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW		V-HIGH	V-LOW
Constant	0.722***	0.912***	Constant	1.007***	0.828***
	(0.083)	(0.023)		(0.038)	(0.020)
$\lvert R_{exclFAAMG,t}\rvert$	0.205***	0.003	$\lvert R_{exclFAAMG,t}\rvert$	0.098***	0.123***
	(0.050)	(0.057)		(0.034)	(0.033)
$R^2_{exclFAAMG,t}$	0.006	0.185***	$R^2_{exclFAAMG,t}$	0.012**	0.020*
	(0.006)	(0.047)		(0.005)	(0.011)
$CSAD_{FAAMG,t}$	2.422***	1.927***	$CSAD_{FAAMG,t}$	2.245***	1.979***
	(0.549)	(0.339)		(0.569)	(0.300)
$R^2_{FAAMG,t}$	0.002	0.006	$R^2_{FAAMG,t}$	0.004	−0.001
	(0.006)	(0.005)		(0.007)	(0.005)
Observations	603	1,734	Observations	1,048	1,289
R^2	0.532	0.192	R^2	0.366	0.216
Adjusted R^2	0.529	0.190	Adjusted R^2	0.364	0.214
Residual Std. Error	0.327 (df = 598)	0.284 (df = 1729)	Residual Std. Error	0.346 (df = 1043)	0.236 (df = 1284)
F Statistic	169.910*** (df = 4; 598)	102.430*** (df = 4; 1729)	F Statistic	150.802*** (df = 4; 1043)	88.430*** (df = 4; 1284)
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

Hypothesis #3

Table A.18: Estimates of herding under extreme market conditions based on 7-day moving averages, year 2020

	Dependent variable:			*Dependent variable:*	
	$CSAD_{2020}$			$CSAD_{2020}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW		V-HIGH	V-LOW
Constant	1.144***	1.315***	Constant	1.357***	1.216***
	(0.125)	(0.078)		(0.104)	(0.051)
$\lvert R_{m,2020}\rvert$	0.172***	0.150	$\lvert R_{m,2020}\rvert$	0.234	0.155***
	(0.064)	(0.138)		(0.155)	(0.041)
$R^2_{m,2020}$	0.008*	0.033	$R^2_{m,2020}$	−0.009	0.012***
	(0.005)	(0.021)		(0.017)	(0.003)
Observations	80	166	Observations	104	142
R^2	0.624	0.230	R^2	0.183	0.581
Adjusted R^2	0.614	0.221	Adjusted R^2	0.167	0.575
Residual Std. Error	0.446 (df = 77)	0.540 (df = 163)	Residual Std. Error	0.638 (df = 101)	0.398 (df = 139)
F Statistic	63.952*** (df = 2; 77)	24.345*** (df = 2; 163)	F Statistic	11.289*** (df = 2; 101)	96.543*** (df = 2; 139)
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

Table A.19: Estimates of herding under extreme market conditions based on 90-day moving averages, year 2020

	Dependent variable:			*Dependent variable:*	
	$CSAD_{2020}$			$CSAD_{2020}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW		V-HIGH	V-LOW
Constant	0.750**	1.473***	Constant	1.576***	1.347***
	(0.335)	(0.112)		(0.125)	(0.078)
$\lvert R_{m,2020} \rvert$	0.366**	−0.013	$\lvert R_{m,2020} \rvert$	0.127	0.069
	(0.171)	(0.133)		(0.105)	(0.071)
$R^2_{m,2020}$	−0.006	0.080	$R^2_{m,2020}$	0.009	0.018
	(0.012)	(0.044)		(0.009)	(0.010)
Observations	47	116	Observations	66	97
R^2	0.565	0.051	R^2	0.395	0.173
Adjusted R^2	0.545	0.034	Adjusted R^2	0.376	0.156
Residual Std. Error	0.643 (df = 44)	0.510 (df = 113)	Residual Std. Error	0.709 (df = 63)	0.397 (df = 94)
F Statistic	28.528*** (df = 2; 44)	3.053* (df = 2; 113)	F Statistic	20.576*** (df = 2; 63)	9.862*** (df = 2; 94)
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

Table A.20: Estimates of herding under extreme market conditions based on 180-day moving averages, year 2020

	Dependent variable:			*Dependent variable:*	
	$CSAD_{2020}$			$CSAD_{2020}$	
	$\hat{\sigma}^2$,HIGH	$\hat{\sigma}^2$,LOW		V-HIGH	V-LOW
Constant	−1.213	1.451***	Constant	1.477***	1.139***
	(1.172)	(0.138)		(0.151)	(0.088)
$\lvert R_{m,2020} \rvert$	1.734**	−0.120	$\lvert R_{m,2020} \rvert$	0.081	0.328
	(0.758)	(0.209)		(0.160)	(0.128)
$R^2_{m,2020}$	−0.226**	0.110	$R^2_{m,2020}$	−0.0004	−0.088
	(0.103)	(0.075)		(0.029)	(0.030)
Observations	5	68	Observations	49	24
R^2	0.441	0.068	R^2	0.033	0.104
Adjusted R^2	−0.118	0.040	Adjusted R^2	−0.009	0.019
Residual Std. Error	0.388 (df = 2)	0.370 (df = 65)	Residual Std. Error	0.408 (df = 46)	0.239 (df = 21)
F Statistic	0.789 (df = 2; 2)	2.388* (df = 2; 65)	F Statistic	0.775 (df = 2; 46)	1.217 (df = 2; 21)
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

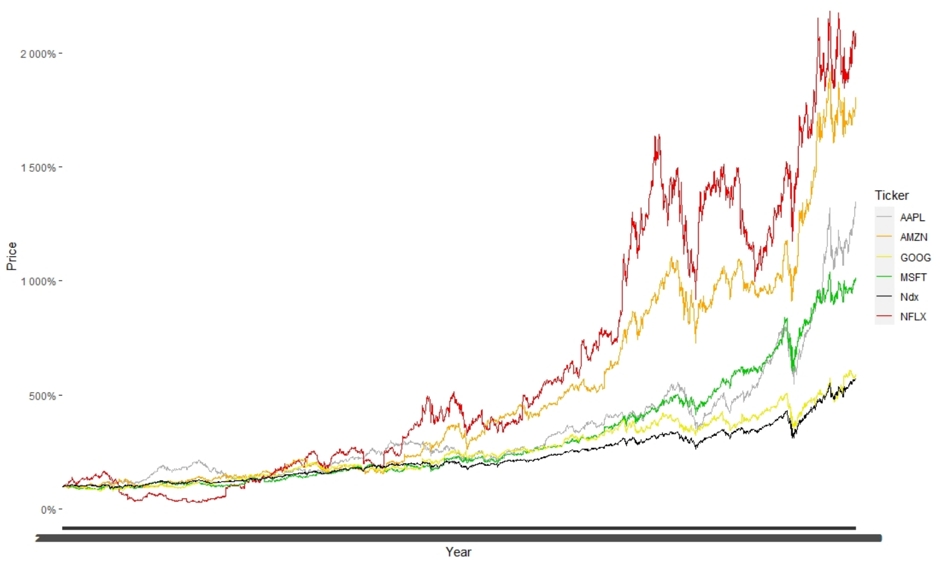
Appended figures

Trading floor

Figure A.1: Development of daily adjusted closing prices ($P_{m,t}$) for NASDAQ-100 index (3/1/2011 – 30/12/2020)

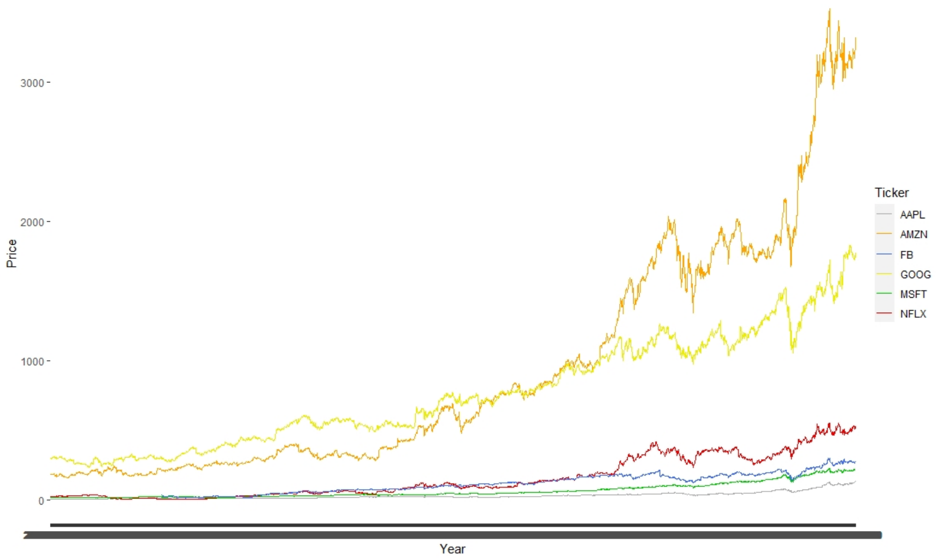
Source: Author's own computations.

Figure A.2: Comparison of stock performances for already listed Big Tech companies in relative to the market benchmark (3/1/2011 – 30/12/2020)



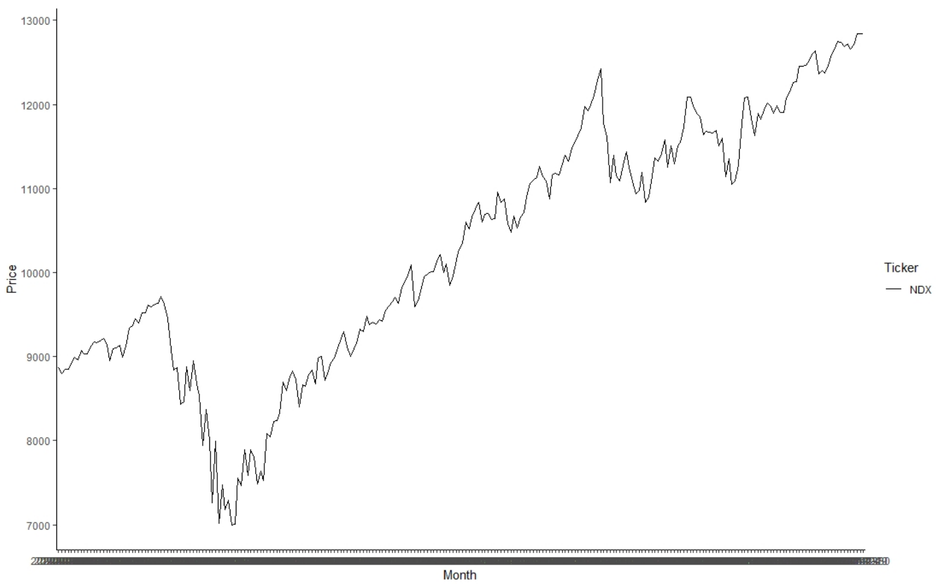
Source: Author's own computations.

Figure A.3: Comparison of stock performances for whole lot of Big Tech companies in absolute terms (18/5/2012 – 30/12/2020)



Source: Author's own computations.

Figure A.4: Development of daily adjusted closing prices ($P_{m,t}$) for NASDAQ-100 index (3/1/2020 – 30/12/2020)



Source: Author's own computations.