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Analysis of Trading Behaviour on Discrete GPU Market: Autoregressive Conditional Duration Approach

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Declaration

I hereby declare that I am the sole author of the thesis entitled “Analysis of Trading Behaviour on Discrete GPU Market: Autoregressive Conditional Duration Approach “. I duly marked out all quotations. The used literature and sources are stated in the attached list of references.

In Prague on .... Signature

Acknowledgement

I hereby wish to express my appreciation and gratitude to the supervisor of my thesis, *Ing. Petra Tomanová, MSc*

Abstract

This bachelor thesis analyses the trading behaviour on the discrete GPU market. First duopoly of AMD and Nvidia is introduced, then its relation with Bitcoin is established in a basic overview. Next, theoretical foundation for Autoregressive Conditional Duration family of models and distributions is given. The empirical part of the thesis first cleans the data then estimates an optimal model for the data from NYSE. The estimated model is then used to analyse the impact of significant events on the observed stocks with an emphasis on changes in Bitcoin price. In conclusion, correlation between both stocks and Bitcoin price has been established.

Keywords

Autoregressive Conditional Duration, Trade durations, high-frequency data, Bitcoin, GPU

Abstrakt

Tato bakalářská práce se zabývá analýzou chování na burze na trhu samostatných grafických karet. Nejprve je představen duopol (AMD a Nvidia), a poté je stanovena spojitost s Bitcoinem v kapitole o této měně. Poté je představen teoretický základ o použitých ACD modelech a rozdělění. V empirické studii jsou nejdříve očištěna data, a poté je odhadnutý optimální model pro data z NYSE. Odhadnutý model je poté použit pro analýzu dopadu významných událostí na sledované akcie. Důraz je kladen na události spojené s vývojem ceny Bitcoinu. Závěrem je čtenářovi dokázána korelace ceny Bitcoinu a dobou mezi obchody obou akcií.

Klíčová slova

Autoregresivní podmíněné durace, Trade durace, vysokofrekvenční data, Bitcoin, Grafické karty

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1. Introduction

Cryptocurrencies are one of the biggest phenomena in trading in recent years. They are digital tokens created by cryptographic algorithms. The most famous one of these tokens is Bitcoin, which was first created in 2009 by an anonymous programmer. In just 8 years this token reached price of almost 20000$ for only 1 Bitcoin *(all bitcoin prices in this thesis are from coinmarketcap.com).* The process of introducing Bitcoins into system is called mining. For this process powerful hardware is needed and while specialised mining devices exist, there are only two options that are easily available to everyone – CPU mining and GPU mining. As GPU mining is a newer and significantly more efficient method of the two it has become the most popular one from all.

This paper will focus on two companies which form a duopoly on the discrete GPU market, as discrete GPUs have superior efficiency to other GPUs. Duopoly is a special case of oligopoly where exactly two companies are present on the market and they react to each other *(Holý and Černý 2016)*. The two companies in this case are Nvidia, which throughout the observed time period dominated the market, and AMD. Analysis of correlation between the two stocks in the time period of 2015 to first quarter of 2018, their impact on each other and their dependence on other external factors such as releases of new products, announcements of new products or issues of at least one of the observed companies, and the development in time of everything above, will be conducted in an empirical study. Special attention will be given to reliance on Bitcoin price as the main hypothesis of this paper is that Bitcoin price is a strong external factor for both of the observed stocks.

Autoregressive conditional duration approach will be used in this paper, I shall attempt to model the trade durations between trades on the NASDAQ stock exchange and fit those durations with the family of ACD models first described by Engle and Russel in 1998 (durations in this case mean time difference between two entries in the database). More advanced models with assumptions of different distributions or different types of parameters followed. Shorter durations signal higher liquidity of the stock, which is one of the most important factors for intra-day traders as it allows them to close their trading position easier.

In the first part of this paper I will introduce the reader to both observed companies. I will also briefly present basic information about Bitcoin mining. Theory about all models and distributions from which the best theoretical model will be selected shall follow. Empirical part of the work will focus on graphical representation of the fitted model for the reader.

For this the model has to be correctly estimated which means longer duration will more likely result in long duration and vice versa, As ACD models are not generally used on their own, this study serves as a baseline for ACD-GARCH *(Engle and NG 1993)* model for price/return modelling.

2. Market Overview

2.1. Observed stocks

2.1.1. AMD

AMD (Advanced Micro Devices Inc.) is an American hardware company founded in 1969. They have entered the GPU business in 2006 with an acquisition of the ATI company. Currently AMD is the second largest company on the CPU market after Intel and the second largest company on the discrete GPU market after Nvidia and its stock is valued at 28,22 dollars apiece. The company however has just finally left the long period of slump – in the worst part of year 2015 the stock price was only 1,62 dollars. Its restructuring throughout the years 2014 and 2015 avoidance of controversies and to a major extent a very good performance of bitcoin saved the company in 2017 and 2018. AMD's current portfolio of products available at retail stores consists of AMD Radeon GPUs, AMD Ryzen and AMD FX CPUs (Ryzen is AMD's top end line of products, while FX offers value for money) and AMD A series APUs (APU is a chip that combines both CPU and GPU) *(www.amd.com)*

2.1.2. Nvidia

Nvidia corporation is an American technology company founded in 1993. In 1999 Nvidia created a chip that they have called the world's first GPU and they call themselves inventors of GPU ever since. While whether said chip was really the first GPU or not is up to debate, the fact that it was revolutionary remains, as it was considered vastly superior to all other alternatives at the time and it marks the start of Nvidia's dominance on the discrete GPU market. Nvidia in the period described in this paper was amidst its "golden age". Up till the Q1 2018 Nvidia reported record financial performance in almost every quarter, their products were known for unrivalled quality and Nvidia's stock was very popular between traders for its stability. While Nvidia's perfect track record changed in recent years and new challenges are presented by a new formidable competitor on the market, Nvidia's dominance over the discrete GPU market remains undisputed till this day. Nvidia's current line up of commonly available products consists of Tegra GPU chips for mobile devices, GeForce series for PC, which is currently advertised as graphical cards for gamers, Quadro which consist of GPUs for professional use in the technology in design and lastly Tesla series which are intended for supercomputers. *(nvidia.com, geforce.com) Information about both stocks from (finance.yahoo.com)*

2.2. Bitcoin

2.2.1. Characterization

Bitcoin is a decentralized digital currency based on cryptography. No person or company controls or supports Bitcoin, it is not based on gold like common currencies are. It is a programme developed in 2009 by unknown programmer, its complex architecture makes it as of the release date of this paper practically impossible to falsify. Bitcoin operates through a peer-to-peer network, without a central server. All devices in this network are called its nodes. Each node in the network may send and trade Bitcoins as much they want. Nodes check the transactions and record them in a public record of transactions named Blockchain. Other than all other normal functions Bitcoin also serves as a reward of Bitcoin mining, which is a process described in one of the chapters below. Transactions are secured with script language and they're realized with a Bitcoin wallet, where they are digitally signed. *(Franco 2015 ch. 1-2)*

2.2.2. Blockchain

Blockchain is a public record of Bitcoin transactions. Blockchain is implemented as a chain of blocks, where each block includes hash function of the previous block. Hash function is a function that codes the data of a random size to one with a fixed size. Transactions are accepted every 10 minutes into blockchain, and they are added as blocks in groups. Accepted blocks are sent to each node for control. *(Franco 2015 ch. 7)*

2.2.3. Bitcoin mining

While the word mining may imply that the process involves finding lost Bitcoins scattered around the internet, which is a common misconception, in reality Bitcoin mining is a mechanism that serves to keep Blockchain entries correct. The purpose is to keep blockchain complete and consistent and with no duplicate entries. For block to be accepted by the rest of the network, miners have to find a block's value called nonce which is then together with the block checked by rest of the nodes in the network. While the check happens very fast, finding the nonce value requires extensive computing time for a very large amount of nonce values have to be tried before a right one is found. These mechanisms exist to make edits to blocks as complicated as possible. Each time nonce is found and the check confirms its validity, the miner is awarded with a set amount of newly created bitcoins. This reward was equal to 50 BTC in the year 2009 however it halves for every 210000 discovered blocks. Current reward is 12,5 BTC. *(Franco 2015 ch. 9)*

3. ACD Models

The family of ACD (Autoregressive conditional duration) models was first introduced by Engle and Russel in 1998 to model probability of an event at each point in time. The general equation of ACD models is:

$$x_i = \psi_i \varepsilon_i$$

where time dependence is described by the function ψ_i called conditional mean duration is identically distributed as x_i, meaning that ψ_i satisfies the conditions

$$\psi_i = E[x_i | x_{i-1}, \dots, x_1; \theta]$$

$$x_i \stackrel{d}{=} \psi_i$$

and ε_i which is a random variable from a distribution that must be specified. This empirical study uses two different distributions for the random variable. The first one is exponential distribution as interval between two consecutive random events is a typical example for the said distribution:

$$f(\varepsilon) = e^{-\varepsilon}.$$

The second one is Weibull distribution (Weibull 1951) used for its ability to take multitude of shapes depending on its parameters.

$$f(\varepsilon) = \theta\gamma\varepsilon^{\gamma-1}\, e^{-\theta\varepsilon^{\gamma}}$$

The Weibull distribution also nests the exponential distribution for γ=1.

3.1. ACD(m,q)

The original ACD model as defined by Engle and Rusell in 1998 *(Engle and Rusell 1997, Engle and Rusell 1998)* as:

$$\psi_i = \omega + \sum_{j=1}^{m} \alpha_j x_{i-j} + \sum_{j=1}^{q} \beta_j \psi_{i-j},$$

where $\alpha_{j,}\beta_j \geq 0,\ \omega > 0, i \in N, j = 1, \dots, m, q$

In the model *m*-memory specification of intensity is given by

$$\psi_i = \omega + \sum_{j=1}^{m} \alpha_j x_{i-j},$$

while the rest of the formula introduces infinite memory by inclusion of q lagged durations. While conditional mean of x_i is equal to ψ_i, unconditional mean is equal to

$$E(x_i) = \frac{\omega}{1-\sum_{j-1}^{m} \alpha_j - \sum_{j-1}^{q} \beta_j}.$$

Variant of ACD(q,m) that uses Weibull distribution is labelled as WACD(q,m)

3.1.1. ACD(1,1)

ACD(1,1) is a special case of ACD(q,m) where both parameters are equal to 1. It is used as a natural starting point while creating ACD models. It is defined as

$$\psi_i = \omega + \alpha_1 x_{i-1} + \beta_1 \psi_{i-1}.$$

ACD(1,1) also requires fulfilment of an additional condition that $\alpha + \beta < 1$. Its unconditional variance equals to

$$\sigma^2 = \mu^2 \frac{1 - (\beta^2 - 2\alpha\beta)}{1 - (\beta^2 - 2\alpha\beta - 2\alpha^2)}.$$

3.2. LACD(m,q)

LACD(m,q) or the logarithmic ACD model, was introduced by Bauwens and Giot in 2000. Thanks to the logarithmization, this model drops the restriction on the parameters α, β and ω allowing it to be more flexible as I do not have to add constraints to ensure the positivity of the equation. For clarity I have decided to include the model as it is written in the documentation of ACDm *(Cran.R)* package for R

$$\ln \psi_i = \omega + \sum_{j=1}^{m} \alpha_j \ln \varepsilon_{i-j} + \sum_{j=1}^{q} \beta_j \ln \psi_{i-j}.$$

Note that the model is described as LACD1(m,q) in the ACDM package, since there is another variant of the model, labelled LACD2(m,q), based on the work of Lunde in 1999 which differs only by the lack of logarithmization in the m-memory specification of intensity .

$$\ln \psi_i = \omega + \sum_{j=1}^{m} \alpha_j \varepsilon_{i-j} + \sum_{j=1}^{q} \beta_j \ln \psi_{i-j}.$$

3.3. AMACD(m,r,q)

The additive and multiplicative ACD model was first described by Hautsch in 2012 as a model that includes both additive and multiplicative innovation component. In his work Hautsch provides what is essentially AMACD(1,1,1) model:

$$\psi_i = \omega + (\alpha \psi_{i-1} + v)\varepsilon_{i-1} + \beta_1 \psi_{i-1},$$

where v is a parameter. If $v = 0$, AMACD is equivalent of a classic ACD model, therefore it can be used in any case ACD model can be used. This work uses a generalized version of the model with parameter vector equal to (m,r,q). It is described by the ACDm R package documentation *(Cran.r)* as

$$\psi_i = \omega + \sum_{j=1}^{m} \alpha_j x_{i-j} + \sum_{j=1}^{r} v_j \varepsilon_{i-j} + \sum_{j=1}^{q} \beta_j \psi_{i-j.}$$

3.4. BACD(m,q)

Box-Cox ACD model was suggested by Hautsch in 2003. It is an additive model based on power transformations of ψ_i and ε_i

$$\psi_i{}^{\delta_1} = \omega + \sum_{j=1}^{m} \alpha_j \varepsilon_{i-j}{}^{\delta_2} + \sum_{j=1}^{q} \beta_j \psi_{i-j}{}^{\delta_1},$$

where $\delta_1, \delta_2 > 0$. The model nests the AMACD and both LACD models with different values of the parameters δ_1, δ_2.

3.5. ABACD(m,q)

Augmented Box-Cox ACD model (Hautsch 2012) combines the exponential ACD model, which is based on the specifications of EGARCH model with the Box-Cox power transformations with additional parameters to find the position and shape of the curve's kink

$$\psi_i{}^{\delta_1} = \omega + \textstyle\sum_{j=1}^{m} \alpha_j (|\varepsilon_{i-j} - v| + c_j(|\varepsilon_{i-j} - b|)^{\delta_2} + \sum_{j=1}^{q} \beta_j \psi_{i-j}{}^{\delta_1},$$

where parameter b gives us the location of the kink while parameter δ_2 determines its shape. While these additions make the model more flexible, its added restriction of $|c| \leq 1$ limits in usability in modelling financial durations.

3.6. SNIACD(m,r,q)

Spline news impact ACD was described by Hautsch in 2012 based on the research by Ng and Engle from 1993, which replaces the impact curve with a linear spline function, with M intervals

$$\psi_i = \omega + \sum_{j=1}^{m} (\alpha_{j-1} + c_0) \varepsilon_{i-j} + \sum_{j=1}^{m} \sum_{k=M}^{r} (\alpha_{j-1} + c_k) 1_{(\varepsilon_{i-j} \leq e_k^-} + \sum_{j=1}^{q} \beta_j \psi_{i-j}.$$

4. Empirical Study

4.1. Data cleaning

Data cleaning is vital in high-frequency data. Hansen and Lunde (2006) have shown that cleaning done well will improve its volatility estimators as the outliers that I get rid of can negatively impact said estimators, while also reducing the size of data. I clean the data using the procedure used for NYSE TAQ by Barndorff-Nielsen et al. (2009). The steps I take are the following:

1. Retain entries originating from a single exchange, delete other entries (NASDAQ in my application, codes D and Q in TAQ User's Guide).

2. Delete entries with the transaction price equal to zero.

3. Delete entries with the timestamp outside the 9:30 am – 4:00 pm window when the exchange is open.

4. Delete entries with corrected trades (Trades with non-zero value of the correction indicator).

5. Delete entries with abnormal sale condition (Trades with other codes than E,F,I and @).

6. If multiple transactions have the same time stamp, use the median price.

7. Delete entries for which the price deviated by more than 10 mean absolute deviations from a rolling centred median (excluding the observation under consideration) of 50 observations (25 observations before and 25 after).

First three steps match with P1-P3 of the cleaning procedure by Barndorff-Nielsen et al. (2009). P1 and P3 are swapped around due to limitations of used computer equipment, however all rules labelled with P are easily interchangeable, so this poses no problem. The first step is used to reduce the impact of time-delays in the reporting of trades and quote updates (Barndorff-Nielsen et al. 2009). It is a step with the highest impact on the data as it reduces the amount of entries by 49,29% on average in the empirical study of this thesis. Second step is used to remove faulty entries from the database, however in this case, this step has not discarded any entries. Third step limits entries to those that were made during trading hours as my empirical study focuses on those, while those are commonly from 9:30 am to 4:00 pm there are some exceptions as noted by table 2. Steps 4 to 6 correspond to Q1 – Q3 in the Barndorff-Nielsen et al. (2009) cleaning procedure. Step four removes all corrected trades from the datafile. Step five removes all transactions that had issues according to NYSE TAQ database. Exceptions are codes E,F and I which symbolize problems that were not significant enough to warrant their exclusion from my data and code @ which is equivalent of transaction with no code and means that no issues were present *(NYSE TAQ user guide).* Step six ensures that no time stamp can be used twice as that is a requirement for the ACD models used in this work. The final step is an adjusted version of Q4 from Barndorff-Nielsen et al. (2009) *(Blasques et al. 2018)* that replaces mid-quote with an actual price to keep it relevant for trade data. The entire cleaning procedure ends with 69,6 % loss of AMD data and 65,0% loss of NVDA data. Progression of the cleaning procedure can be seen in table 1.

Table 1 – Data deletion during cleaning

Step	Number of Entries	
	AMD	**NVDA**
Initial data	62161002	62380576
Deletion of data from other exchanges	28856915	34294136
Deletion of data with price of 0 and with timestamp outside of the trading hours	28399446	33891264
Deletion of corrected trades	28398046	33889240
Deletion of entries with abnormal sale condition	28075134	33668405
Deletion of duplicate timestamps	18964080	21907264
Clean data	18913270	21863924

Table 2 – list of NYSE holidays

2015	2016	2017	2018
1.1	1.1	2.1	1.1
19.1	18.1	16.1	15.1
16.2	15.2	20.2	19.2
3.4	25.3	14.4	30.3
25.5	30.5	29.5	
3.7	4.7	3.7*	
7.9	5.9	4.7	
26.11	24.11	4.9	
27.11*	25.11*	23.11	
24.12*	26.12	24.11*	
25.12		25.12	

Dates labelled with * are the dates when trading hours end at 1PM, other dates are holidays. *(source: NYSE TAQ holiday list)*

4.2. Data characteristics

All data has been taken from NYSE TAQ database. The database stores all trades and quotes for all issues traded on the New York Stock Exchange (NYSE), National Association of Securities Dealers Automated Quotations (NASDAQ) and the regional exchanges from 1993 up to the present. The data used in this study are taken from January of 2015 to March of 2018 and two different stocks are analysed. One of them is Advanced Micro Devices, Inc. (AMD), the other is Nvidia Corporation (NVDA). All of the used data is high-frequency, meaning that the a new entry is recorded in every minute or less. NYSE TAQ uses tick-by-tick data with millisecond accuracy. Thanks to that high-frequency data offers a very high statistical value

(Dacorogna,2001). Base data consists of 62161002 entries for AMD stock and 62380576 entries for NVDA stock. Descriptive statistics of trade durations of both stocks can be seen in Table 3.

Table 3 – Descriptive statistics of trade durations of AMD and NVDA stocks

	AMD	**NVDA**
n	18913270	21863924
Mean	1,005	0,869
Minimum	0,001	0,001
Median	0,097	0,116
Maximum	1422,961	894,701
Variance	11,423	6,773

4.3. Daily intensity

Figures 1A and 1B show trading intensity during 4 selected days for both observed stocks. Lowered trading intensity around 12PM caused by lunch breaks are notable. The days in which the trading intensity strongly differs between morning and afternoon are the days in which the bid price changed a lot. For example, on 1st December of 2016 NVDA stock price fell by 4,84%, while on 1st June of 2015, the price changed only by 0,49 %.

Figure 1A - Daily trading intensity for selected days estimated by kernel density – AMD Stock

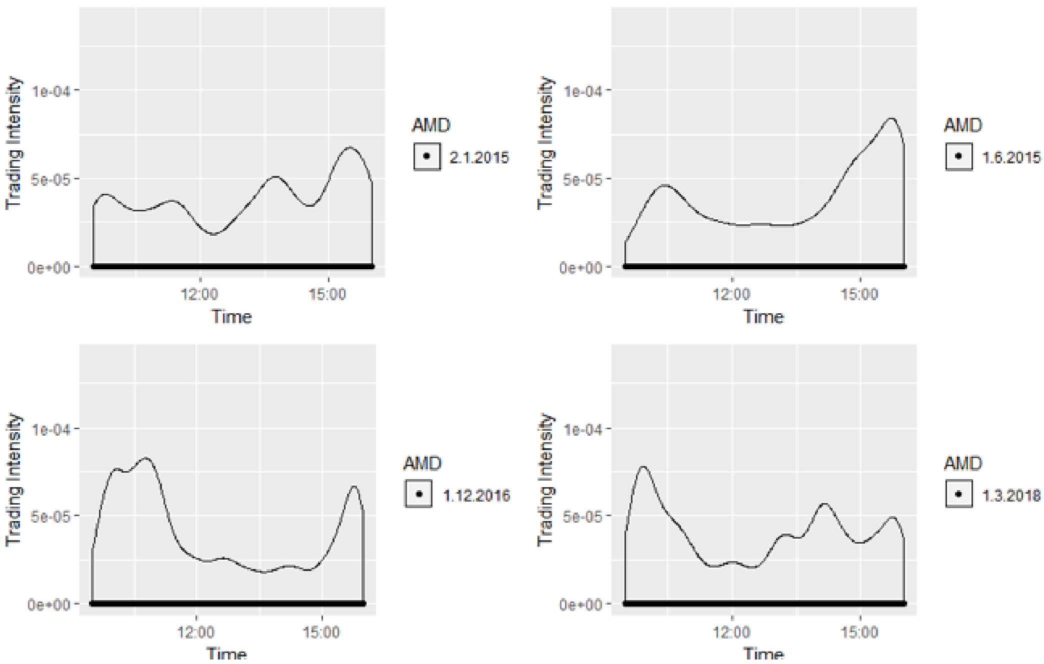
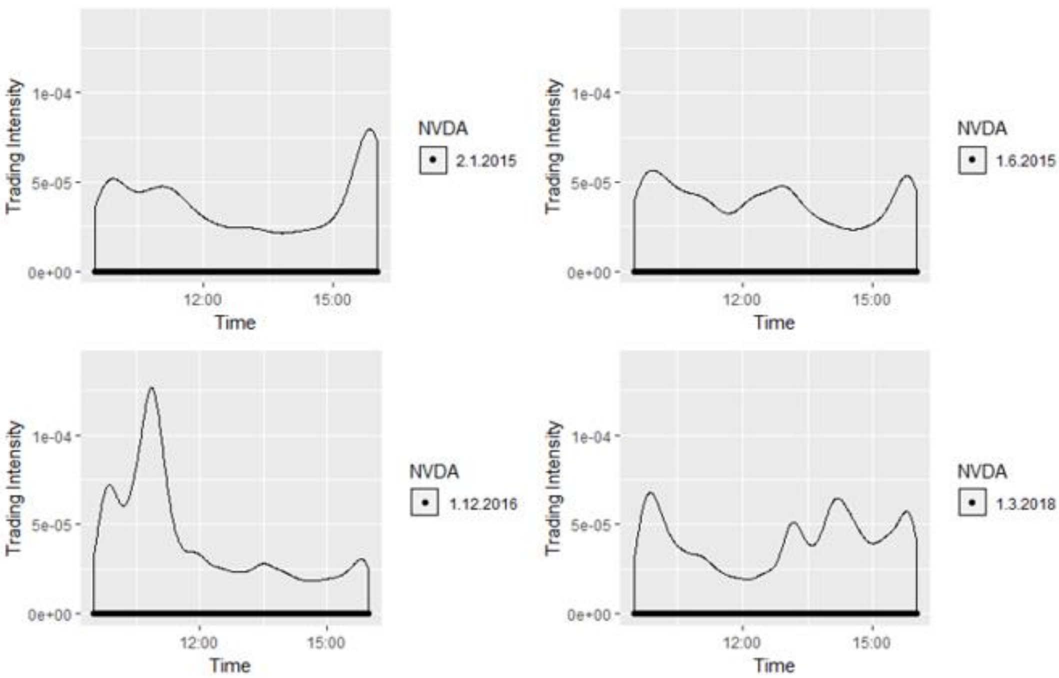


Figure 1B - Daily trading intensity for selected days estimated by kernel density – NVDA Stock



4.4. Model estimation

Cleaned data formatted as durations has been fitted on all of the models described in more detail in the theoretical part of this paper *(Žikeš and Bubák 2006)*. As the cleaned data is still very large LACD1, LACD2. BACD and ABACD models cannot be used with the available equipment, therefore they have not been estimated. The remaining models have been estimated in R using the ACDm package *(Cran.r)* with Optimization Using PORT Routines as an optimization function. The models have then been compared using the Akaike information criterion (AIC) defined by Akaike (1974) as

$$AIC = 2lnL * k,$$

where k is the number of parameters and lnL is the log likelihood. The models with lower AIC value have a better fit, other than that AIC's value does not tell us anything. Table 4 shows estimated parameters and AIC of all models.

Table 4 – ACD model estimations

ACD			**AMACD**		
	AMD	**NVDA**		**AMD**	**NVDA**
ω	0,0029	0,000362	ω	0,00167	-0,00224
α	0,1138	0,057747	α	0,09472	0,04861
β	0,8935	0,945193	β	0,0144	0,94963
			ν	0,89302	0,00444
AIC	1.454636e+07	1.555763e+07	AIC	1.408705e+07	1.537980e+07

SNIACD			**WACD**		
	AMD	**NVDA**		**AMD**	**NVDA**
ω	0,00875	-0,00765	ω	0,0164	0,00613
β	0,92982	0,97047	α	0,6018	0,24178
c0	0,06688	0,03152	β	0,6031	0,80742
c1	-0,0535	-0,03769	γ	0,4425	0,46518
c2	0,0805	0,05741			
AIC	1.650047e+07	1.739262e+07	AIC	1.549206e+07	1.231737e+07

The results show that AIC is lowest for WACD (standard ACD model with Weibull distribution of the random variable ε) in NVDA's case and AMACD for AMD stock. To model both stocks with the same model, WACD was selected. Table 5 shows standard errors in the models. It is clear that both ACD and WACD models have no issues with them, however basic ACD model shows smaller standard errors. The remaining two models could not calculate standard errors for NVDA, therefore they would not be used even if their AIC would be lower than in WACD's case.

Table 5 – Standard errors in estimated models

ACD			AMACD		
	AMD	NVDA		AMD	NVDA
ω	0,0000	0,0000	ω	0,0000	-
α	0,0001	0,0001	α	0,0001	-
β	0,0001	0,0001	β	0,0000	-
			ν	0,0001	-
SNIACD			**WACD**		
	AMD	NVDA		AMD	NVDA
ω	0,0000	0,0000	ω	0,0000	0,0000
β	0,0001	-	α	0,0010	0,0005
c0	0,0002	-	β	0,0004	0,0003
c1	0,0002	-	γ	0,0001	0,0001
c2	0,0001	-			

The autocorrelation functions for both stocks (Figure 2A, Figure 2B) show very long memory based on the hyperbolic decay of the autocorrelation structure

Figure 2A - ACF and PACF – WACD(1,1) AMD

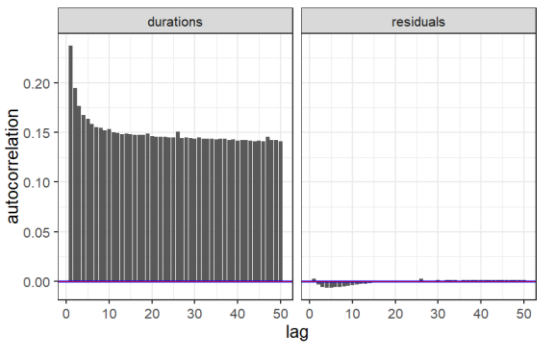
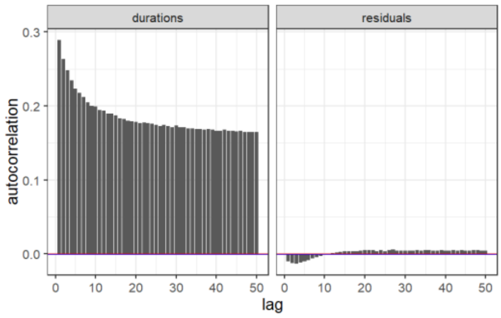


Figure 2B - ACF and PACF – WACD(1,1) NVDA



4.5. Data Analysis

This part of this paper will focus on differences between fitted durations in time and it will try to explain said differences during various events with focus on Bitcoin price and its development. As this study works with a very big amount of data, all graphs show only the trading hours of a single day, any larger period that cannot be shown in an efficient manner. All graphs in the following part consist of plotted observed durations and a black line that shows fitted durations based on the previously estimated WACD model *(cran.r ggplot2 ggpubr).* Some of the observed durations are dropped from the graphs (always <10). Right graphs show NVDA stock, left ones show AMD stock. This chapter is split by years for better navigation in the paper.

Before the observed timespan, bitcoin prices were declining throughout the entirety of the year 2014. AMD controlled 24% of the market of discrete GPUs while Nvidia controlled the other 76%, no other company is significant on the market during the observed period. As AMD is a company with a smaller market share, it can be expected that the impact of bitcoin price on its stock and sales is going to be higher than on Nvidia's if we assume that AMD and Nvidia GPUs are equally effective in mining bitcoin.

4.5.1. AMD and NVDA in 2015

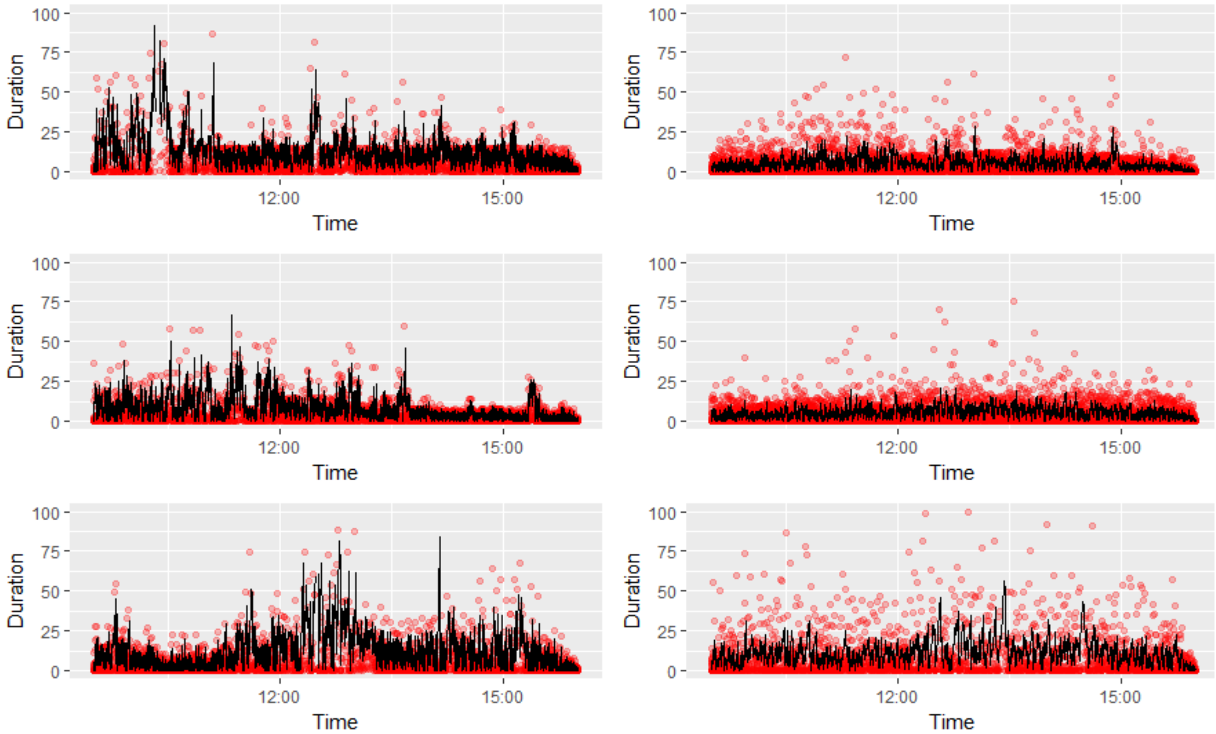
Before I get to impact of bitcoin prices in 2015, I would first like to bring attention to two different situations that happened in the same year on the market. The first one is to show impact of an important card release on the stocks of both companies. It shows one of the rare moments in the observed time period when AMD's release impacts NVDA as it mostly goes the other way around because of the market share. 25th June 2015 marks the release of AMD's flagship card for the year - AMD Radeon R9 Fury X. The card released 22 days after the release of Nvidia's flagship card Nvidia GeForce GTX 980 Ti, while in time the card has been deemed inferior in every aspect to the one made by Nvidia, in short term it made AMD's stock more lucrative for traders as shown by the number of trades as shown on Table 6.

Table 6 – Number of trades during release of AMD Radeon R9 Fury X

Date	AMD	NVDA
11.6.2015	5187	9042
25.6.2015	9791	8026
2.7.2015	9528	4397

On the figure 3 the decrease in duration is apparent between 11th June 2015 and 25th June 2015, while the difference between the first and last described date is not as visible, amount of trades shows as that it is due to some high values during lunch time. Nvidia's stock has not reacted on the release date of AMD's new flagship device, however state at 2nd July 2015 shows that the traders reacted after some time.

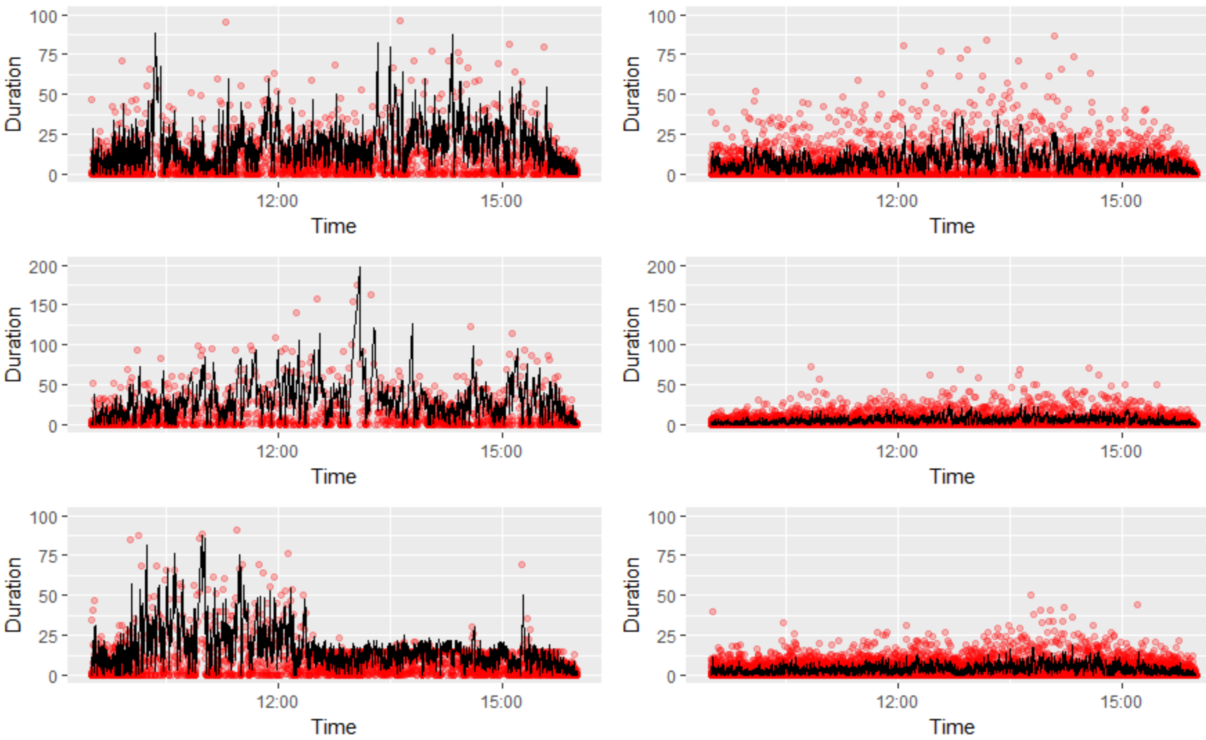
Figure 3 – Effect of AMD's release on NVDA stock



11.6.2015 25.6.2015 9.7.2015

The second situation involves an opposite scenario when Nvidia released its successful GTX 980 card for notebooks, which resulted in quite peculiar behaviour at the release date on the AMD's side.

Figure 4 – Effect of Nvidia's release on AMD stock



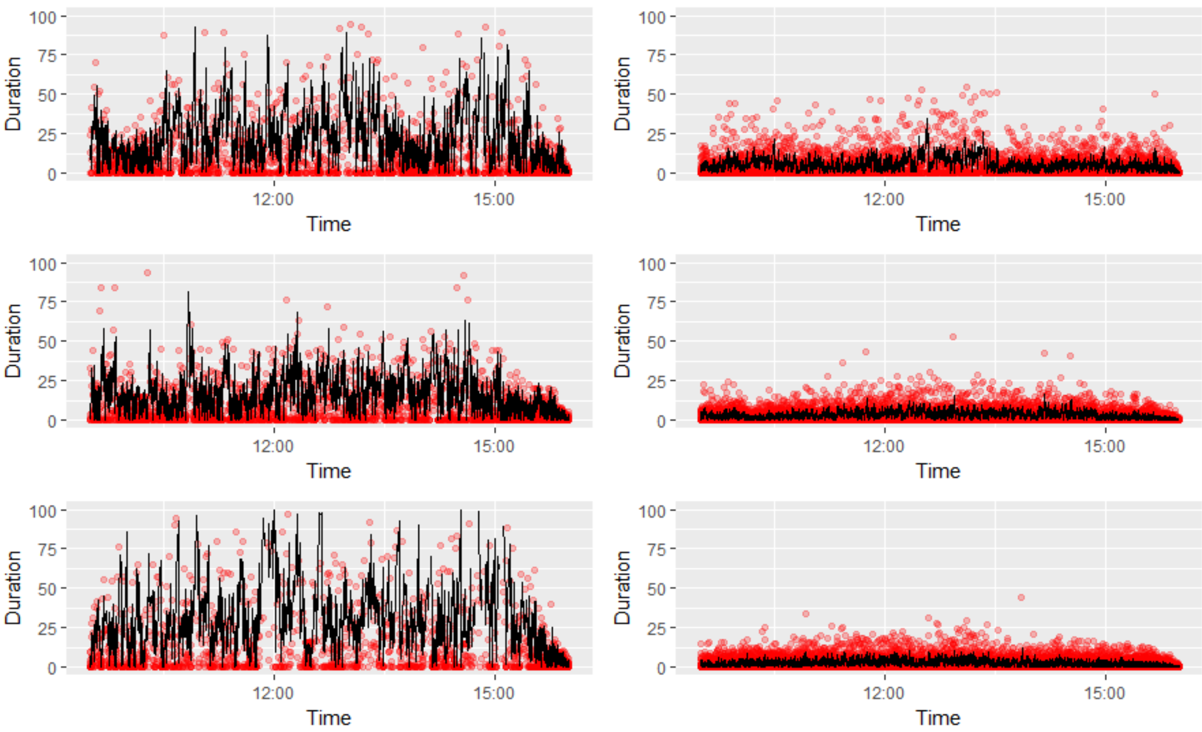
15.9.2015 22.9.2015 29.9.2015

In figure 4 it can be seen that twice as big as usual scale had to be used to capture trade durations for AMD's 22nd September. On the date no outages were reported by either NYSE or AMD, therefore I conclude that Nvidia has higher impact on AMD as vice versa, which confirms its dominant position on the market.

Between 1st January and 30th October Bitcoin's price fluctuated between 200$ - 300$ per 1 BTC, while there was a significant drop in Bitcoin's value in January, I would like to illustrate my case on the time period between 28th October and 11th November when Bitcoin's value rose by 47,2% in a single week from 299,08$ per 1 BTC to 440,16$ per 1 BTC and then dropped by 26,3% to 324,12$ per 1 BTC in course of another. The expected scenario of drop and subsequent increase in duration can be observed well on the AMD stock graphs on Figure 5. Nvidia does not seem to be affected as much mainly as in spite of the Bitcoin's volume drop the number of trades actually further increased. That is caused by not only the release of Nvidia's Jetson TX1 developer kit which was a completely new product, Nvidia also had a very successful year and was less reliant on alternative uses of their GPUs. Figure 5 reflects all of these facts accurately.

At the end of the year Nvidia's market share was 78,8% making the company's position even more dominant than it previously was. Bitcoin's value started its linear growth trend it maintained for over year.

Figure 5 – Effect of changes in Bitcoin price on stocks

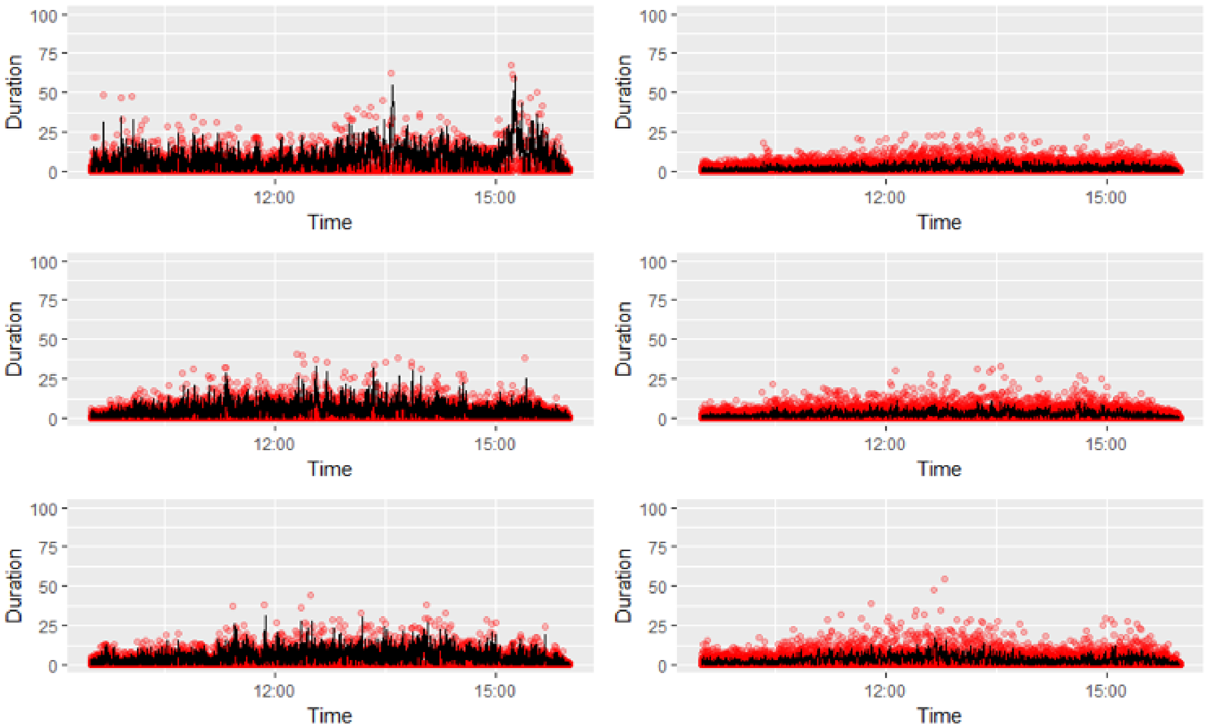


28.10.2015 4.11.2015 11.11.2015

4.5.2. AMD and NVDA in 2016

On the figures from the year 2016, I would like to further demonstrate the impact of Bitcoin's price on few standard situations in its changes. The price was relatively stable for the first 5 months of the year however in the period between the end of May and the beginning of August some significant spikes were present. The first figure (figure 6) marks the period's first surge in Bitcoin's price. Trade durations of NVDA's stock show little change, on the other hand there is a significant decrease in durations on AMD's side, even though AMD released no new products in the displayed time period.

Figure 6 – Effect of rise of BTC's price on stocks

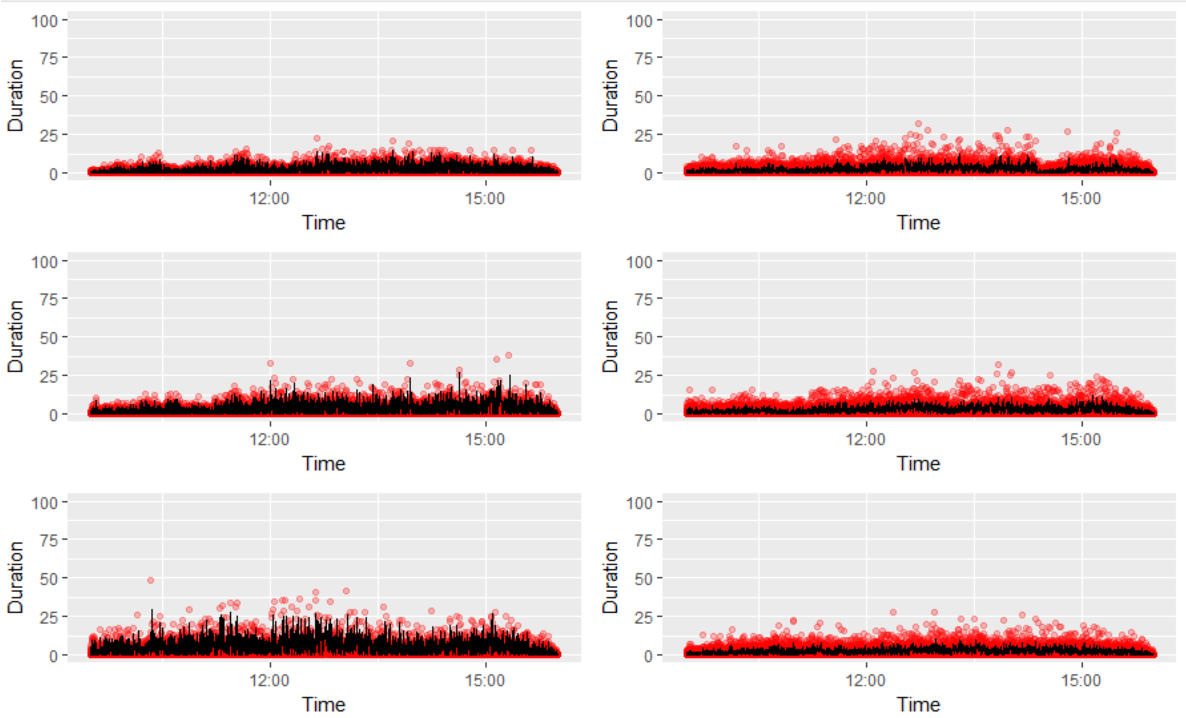


17.5.2016 24.5.2016 31.5.2016

The figure 7 shows an opposite scenario from when the Bitcoin's price plummeted by approximately 100$ per 1 BTC in just 7 days from 26th July 2016. The figure also shows lasting negative effect on the trade durations as the price has not quite regained its previous level until the end of the year. These two figures confirm that the behaviour described in the earlier parts of this empirical study matches the results of the fitted model although before the year 2017, it is not as clear on the Nvidia's stock. Same was confirmed for different major increases and decreases throughout the observed time period, showing all of those cases however would be redundant.

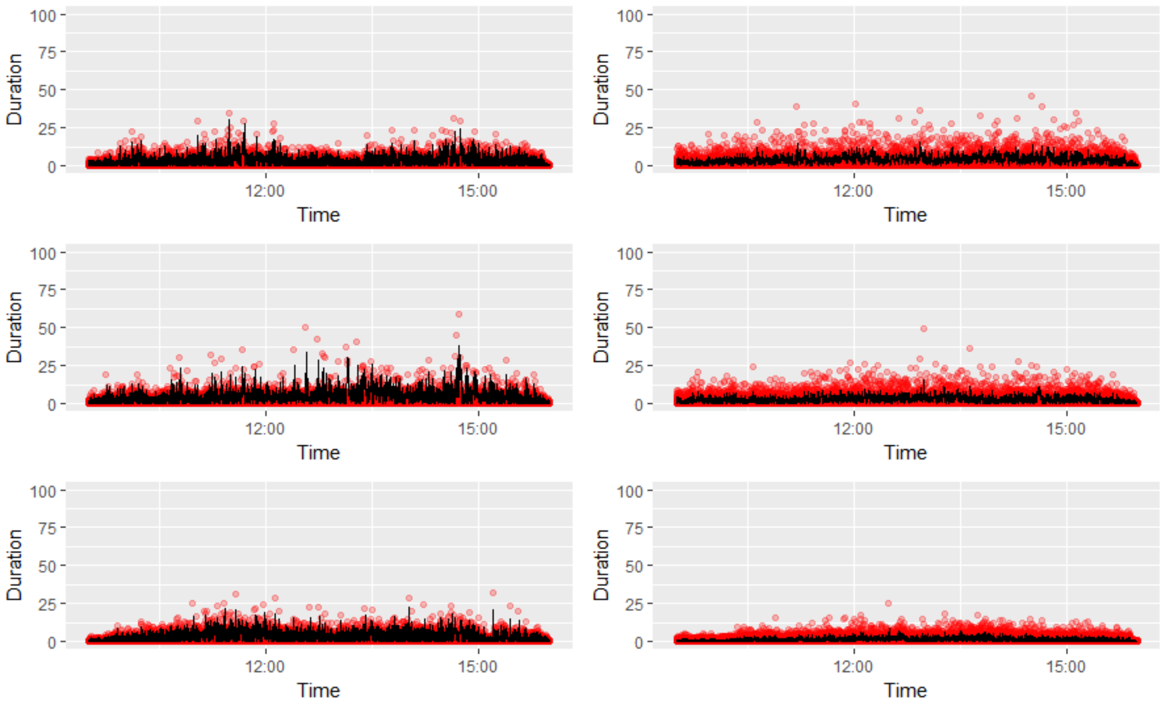
To prove that reactions to changes in Bitcoin prices are immediate I present figure 8 where I can see longer durations on the second day of the three displayed. During those three days price has not changed by a large margin between 23rd June and 25th June, however it was significantly lower on 24th June.

Figure 7 – Effect of fall of BTC's price on stocks



26.7.2016 2.8.2016   9.8.2016

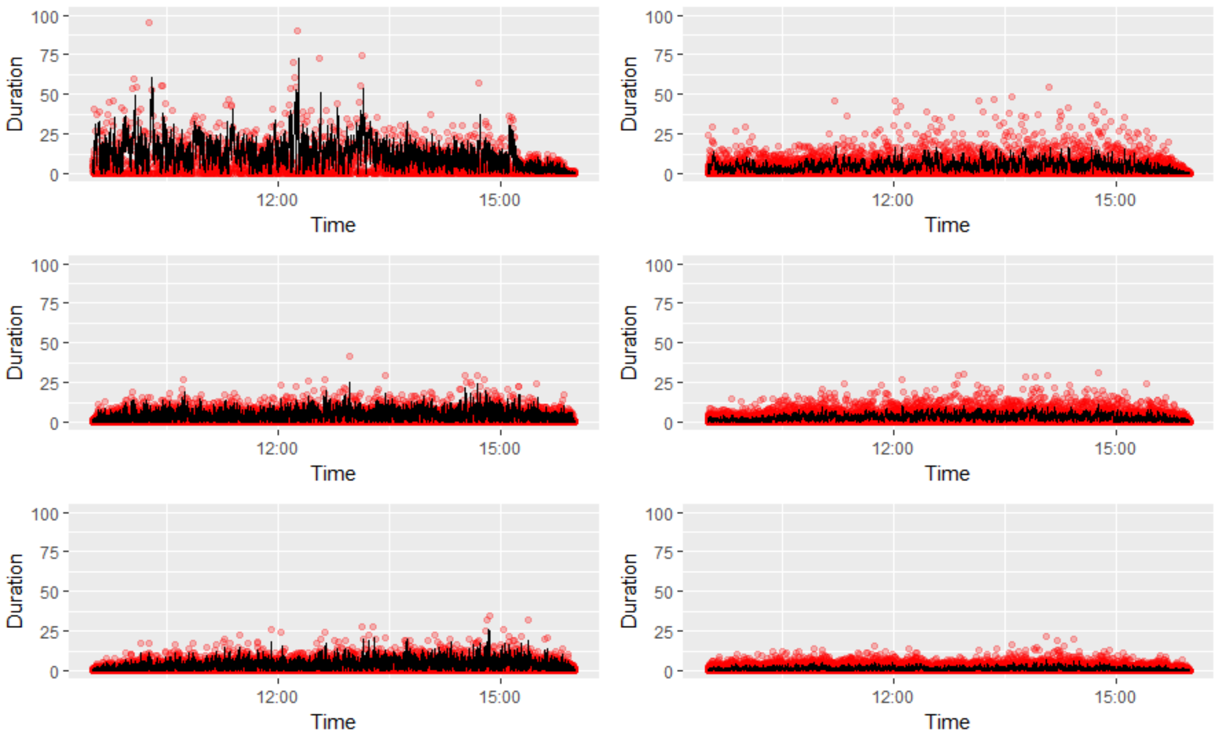
Figure 8 – Proof of traders' instant reactions to changes in Bitcoin prices



9.6.2016 23.6.2016 7.7.2016

Up till this point graphs were only AMD's stock confirmed my initial hypothesis were presented. I therefore present another set of graphs on figure 9 from different points of time during the year 2016. 29th January and 23rd December were selected due the respective lowest and highest prices of the year during those days when we exclude holidays and weekends, the remaining date was chosen randomly. While all differences cannot be credited to BTC prices alone, it is bound to be a significant factor as the discrete GPU market shared by AMD and Nvidia should logically be declining over time with the increasing popularity of notebooks and other electronic devices and the market for GPUs for those devices is dominated by other companies.

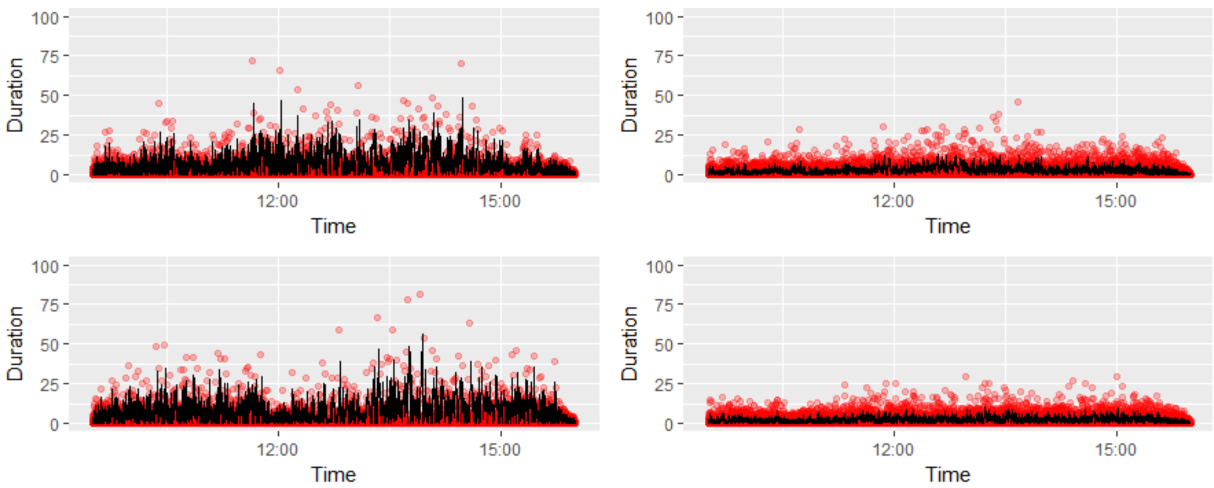
Figure 9 – Durations throughout the year 2016



29.1.2016 6.9.2016 23.12.2016

The next figure (figure 10) I would like to show for the year 2016 shows the effects of announcment of the new card by Nvidia. As it can be seen the effects of announcments of new products show a familiar phenomenon as the release of the new product had the same occurrence. These graphs are also shown to show that the occurrence from the year 2015 was not random.

Figure 10 – Announcement of Nvidia's new card



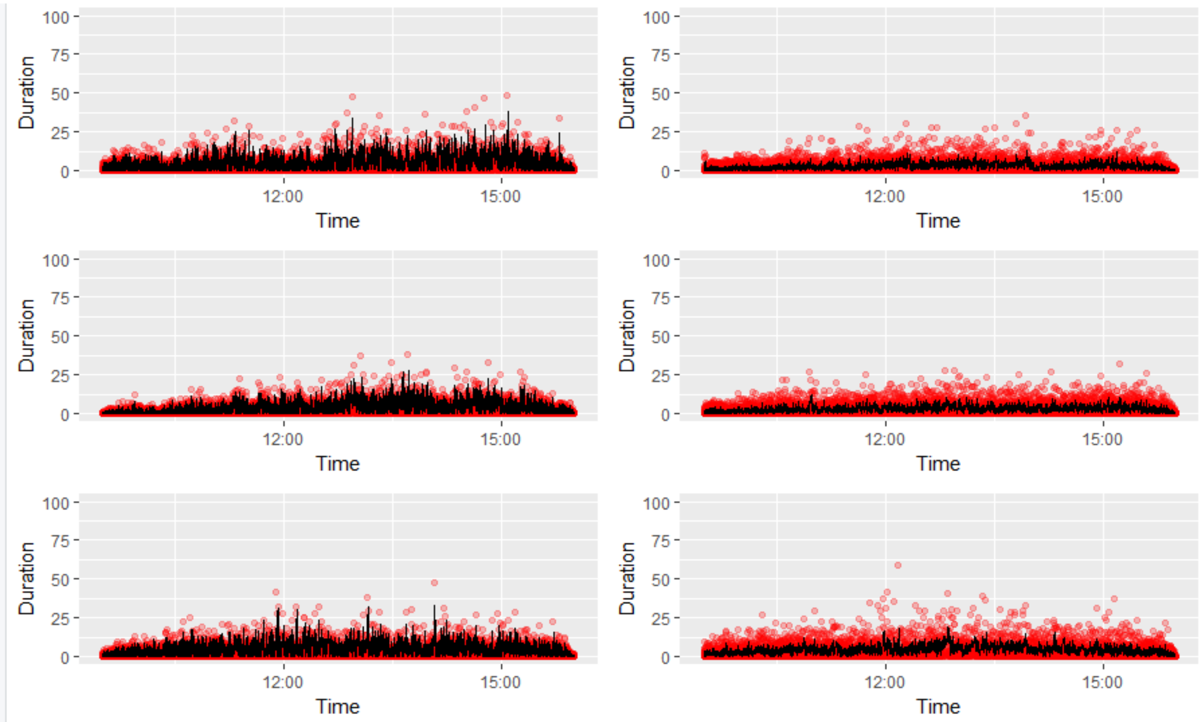
6.7.2016 7.7.2016

The last figure for year 2016 that I would like to discuss is showing the effect of a new cooperation. On 14th October 2016 AMD struck deal with Alibaba, world's largest retailer and e-commerce companies *(marketwatch.com).* This allowed AMD to become one of the most traded stocks for a brief time period. The effects are further shown in table 7 and figure 11.

Table 7 - Number of trades during release of AMD's deal with Alibaba

Date	AMD	NVDA
12.10.2016	15606	15917
14.10.2016	29652	14363
17.10.2016	15440	9444

Figure 11 – Durations during the announcment of AMD's cooperation with Alibaba



12.10.2016 14.10.2016 17.10.2016

4.5.3. AMD and NVDA in 2017

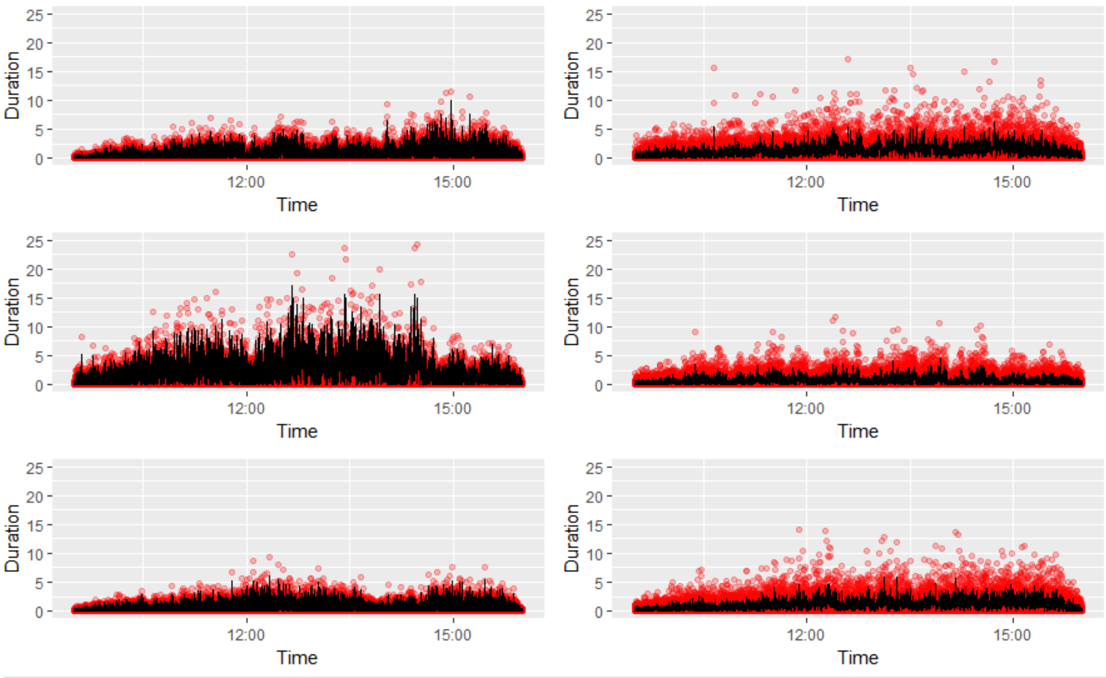
Year 2017 is characteristic by the exponential growth of Bitcoin price, which culminated on 17th December, when it hits its all-time high of 19783,21$ per 1BTC (note that Bitcoin's first recorded price of 2017 was shy of 1000$ per 1BTC). This chapter will focus on more common scenarios of changes in BTC price and the large spike in price from the end of the year, it will also introduce the reader to some other impactful factors.

During the period between 7th and 21st June several things happened that caused changes in trade durations. On 14th June 2017, Bitcoin price dropped by several hundred dollars which is well reflected by the data from AMD stock (figure 12), durations in Nvidia's case show the opposite development as Nvidia just announced its financial results in Q1 *(nvidianews.nvidia.com)*, which were by far the best ones yet. While the bitcoin's prices recovered before 21st June, the resurgence of trading of AMD stock should be mainly credited to the success on a different market, as AMD saw success on CPU market with their new Epyc server processors. This fact is also well reflected in the Table 8.

Table 8 - Number of trades during June

Date	AMD	NVDA
7.6.2017	96082	35110
14.6.2017	31039	65318
21.6.2017	100334	41287

Figure 12 – Events of June 2017



7.6.2017 14.6.2017 21.6.2017

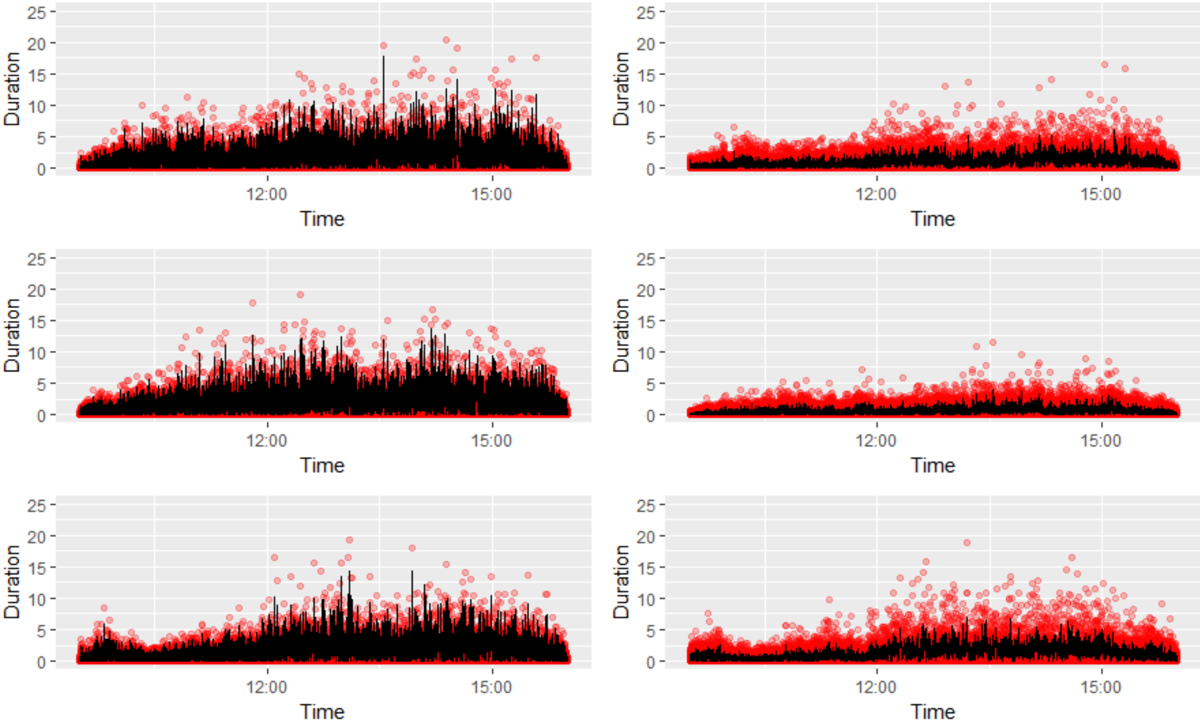
On Figure 13 further connection between observed stocks is established, On 14th August 2017, AMD introduced its generation Vega GPU series, this fact slightly lowered durations between AMD stock trades while increasing the trade durations of Nvidia to the level of AMD.

The most important development in BTC's price in the year happened near the end, during the period between 27th November and 17th December, it has more than doubled. The following table and figure (table 9 and figure14) show the development before and during the rapid growth, strong effect can be seen on both stocks. It can be established that such large swings in price affect the entire discrete GPU market.

Table 9 - Number of trades during the BTC price surge

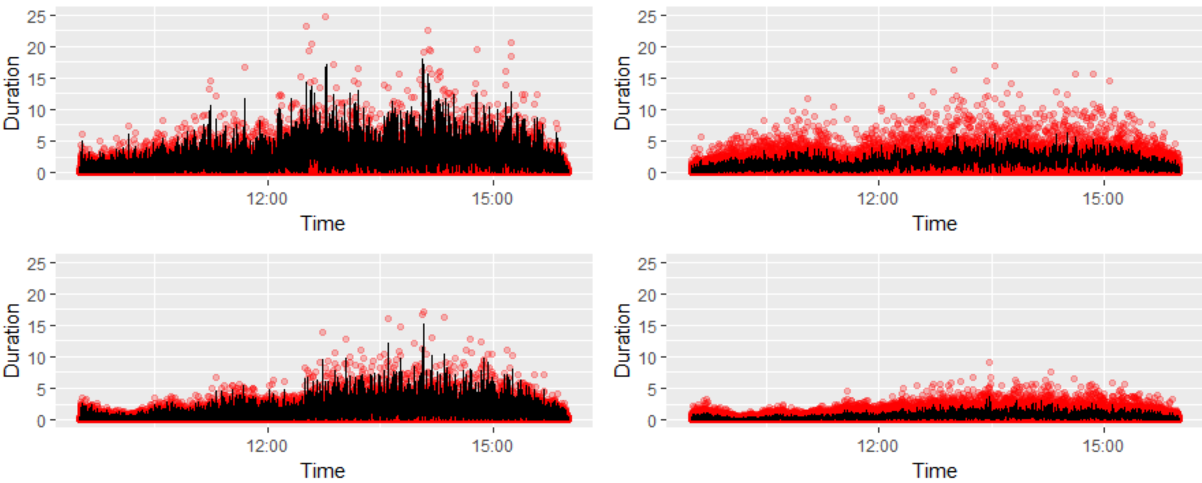
Date	AMD	NVDA
27.11.2017	30306	28676
4.12.2017	68420	98975

Figure 13 – Introduction of AMD Vega



7.8.2017 14.8.2017 21.8.2017

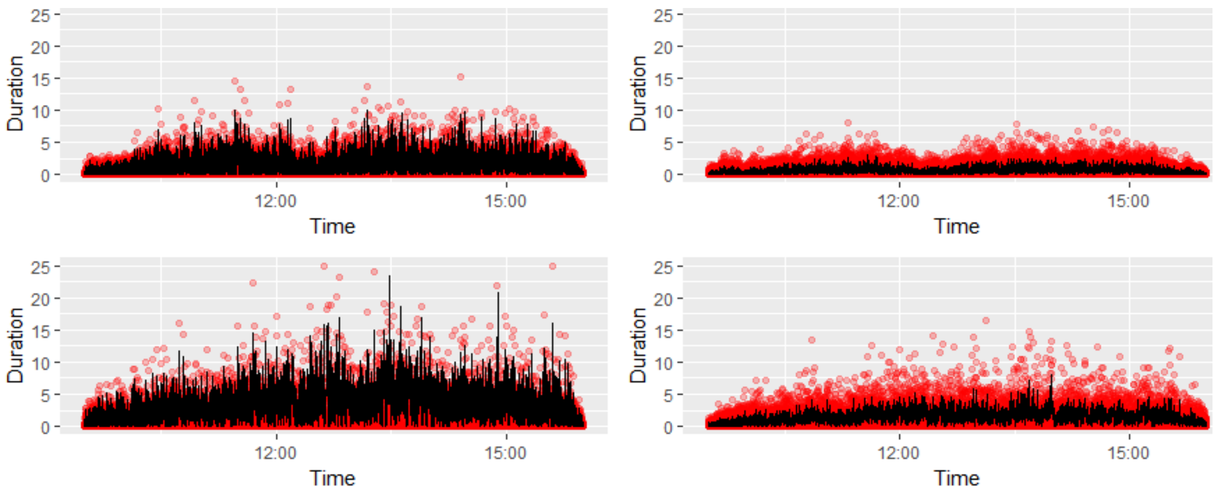
Figure 14 - Durations during the BTC price surge



27.11.2017 4.12.2017

The last figure that I present for the year 2017 is from 9th November 2017. That is the date when executive from AMD Raja Koduri unexpectedly left the company for Intel *(techspot.com)*. While this is not a change that should affect Nvidia, it did, because of the implications of Intel entering the discrete GPU market. Figure 15 shows the situation on the day Raja Koduri left and on another day week later which summarizes the situation in the days between well.

Figure 15 – Raja Koduri's leave



9.11.2017 16.11.2017

4.5.4. AMD and NVDA in 2018

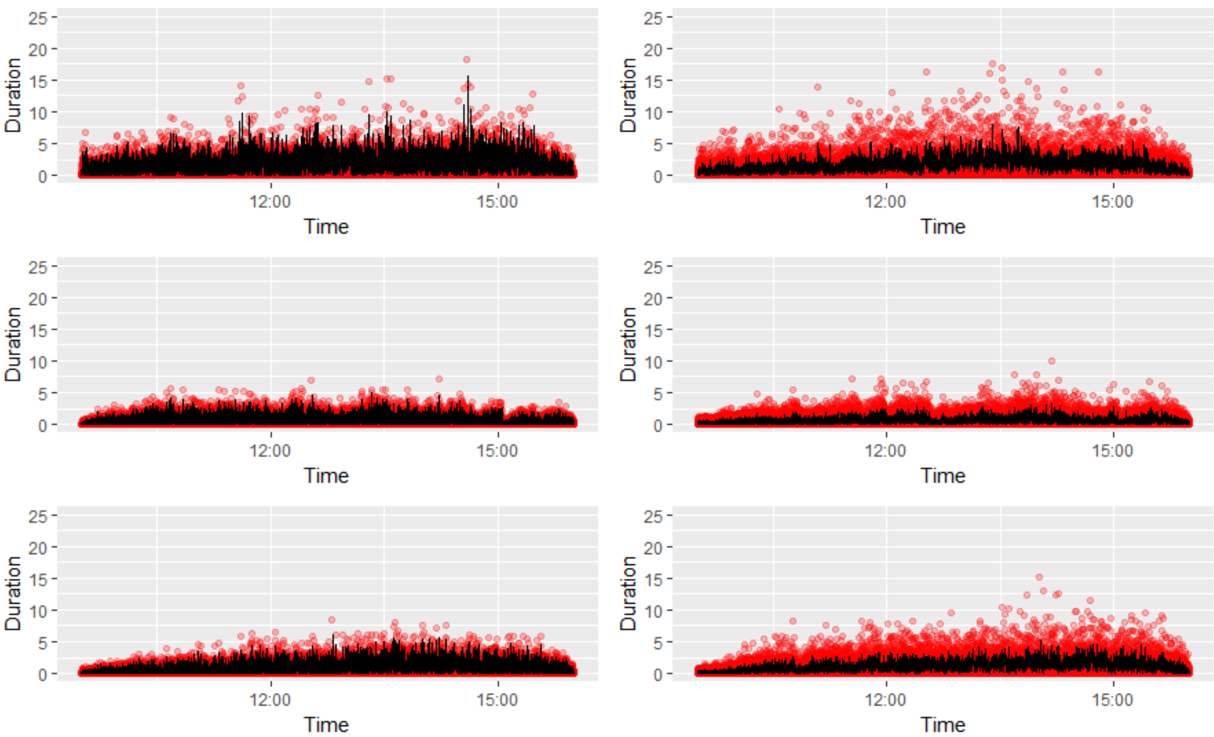
While the available data shows only first quarter of the year 2018, there are still some phenomena to be described. Bitcoin price has been on the decline throughout this period of time, however as that connection has already been discussed enough over the course of this paper, I shall focus on other events instead.

First such event is right from the start of the year. The behaviour where the first day of the year is calm and second sees large quantity of trades might be credited to the time of the year. As table 10 shows however, unexpectedly there are more trades of AMD stocks than Nvidia's stocks. The likely cause is the controversial decision of Nvidia from the end of the previous year, that was reflected by performance on the stock market only after the holiday season was over. Nvidia did not like the fact that companies are using their gaming GPUs instead of the special server GPUs they craft because of the great cost/value ratio. To counterattack the problem, they have decided to ban the use of all gaming GPUs in data centres which caused backlash from costumers (*datacenterdynamics.com)*. Figure 16 shows the situation on graphs.

Table 10 - Number of trades during Nvidia's controversy

Date	AMD	NVDA
2.1.2018	31035	27427
3.1.2018	101352	72120
4.1.2018	78443	46440

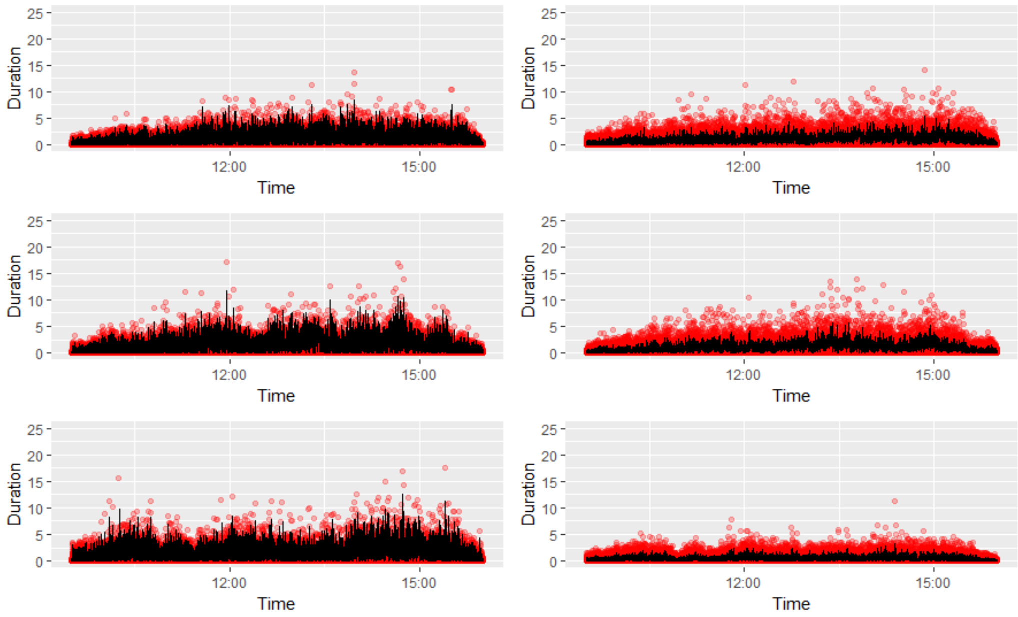
Figure 16 – Start of they year 2018, Nvidia’s ban of GeForce from data centres



3.1.2018 4.1.2018 5.1.2018

Second event was recorded at start of the February, when Nvidia yet again announced record results (Figure 17) *(nvidianews.nvidia.com).* Simultaneously Bitcoin’s price dropped after Facebook banned all cryptocurrency related ads in fear of its users becoming victims of fraud. This action was followed by both Google and Twitter in the following month; there however the effect is harder to observe as other event as described farther occurred.

Figure 17 – Nvidia’s record results, drop in Bitcoin caused by Facebook



29.1.2018 1.2.2018 8.2.2018

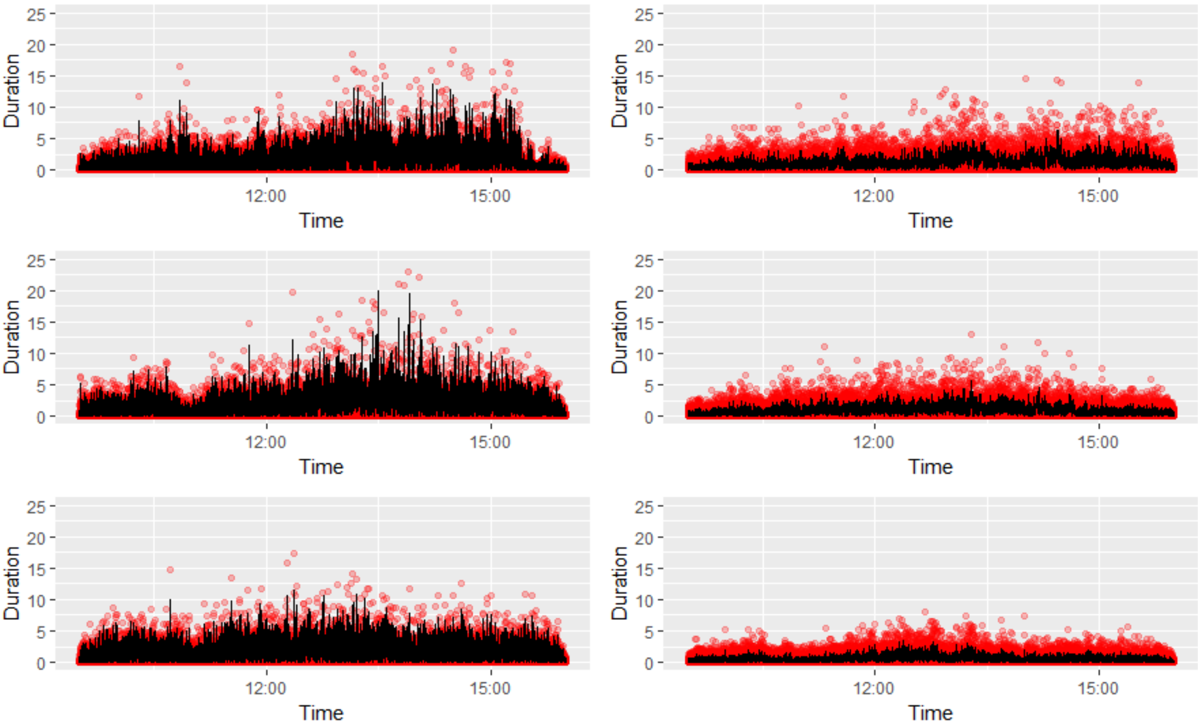
The figure 18 shows effects of attending major conferences on the stock market, both AMD and Nvidia regularly attend GDC (Game Developer Conference) which took part from 19th to 23rd March in the year 2018. However, Nvidia also organizes its own conference GTC (GPU Technology Conference) *(nvidia.com)* which is the biggest GPU centred conference in the world. Shorter durations are apparent on Nvidia’s stock, table 11 also confirms significantly increased NVDA stock trading during the conferences, more so during GTC.

Table 11 - Number of trades during GDC 2018 and GTC 2018

Date	AMD	NVDA
14.3.2018	49188	37375
20.3.2018	36772	46049
28.3.2018	31153	76573

Major spike on 28th March can be observed for Nvidia, curiously though, trading of AMD stock was less frequent during the GDC than before the conference. That is likely caused by bigger involvement of Nvidia in the conference.

Figure 18 – Durations during GDC 2018 and GTC 2018



14.3.2018 20.3.2018 28.3.2018

5. Conclusion

This paper has focused on modelling of trade durations of NVDA and AMD stocks on NASDAQ exchange between 1st January 2015 and 31st March 2018. Before the model was estimated, standardized cleaning of NYSE TAQ database data had to be done. As the remaining datasets still consisted of 18913270 and 21863924 entries respectively, limited number of models was estimated. From those models WACD (1,1) was selected as its AIC value was the lowest across estimated models.

The empirical study has shown that movements in Bitcoin prices indeed had significant impact on the trade durations of both stocks. While the price was rising the durations between trades shortened and vice versa. This was more apparent on the AMD stock and hard to observe on NVDA stock except the most extreme changes in price which were very clear on both. The shortest durations were recorded at the times when the Bitcoin prices were the highest. The market has proven to be lucrative in terms of liquidity as the durations were progressively shorter in the later dates of the dataset.

Both companies also affected each other with releases and announcements of new products. Nvidia's releases affected AMD's stock more than the other way around because of its position of market leader, which was completely uncontested in the observed period. Other significant factors have proven to be conferences which had the same positive effect on both companies with an exception of the conference that Nvidia organizes. Surprising was the effect of a leave of an important AMD executive which negatively affected both stocks because of the implications said action had.

As the data is historical, the model would have to be reestimated for newer data, if it would be used in predictions. Thanks to the fact that the data is historical I can conclude that the model would very likely not be accurate as mere month away from the end of the observed period Nvidia got into a big controversy that made customers and traders question the company's ethics. From that point Nvidia got into more controversies and some of their products were met with backlash. Bitcoin's price was also steadily falling and GPUs sales for the purpose of mining bitcoins dropped rapidly. This shows how significant events move the market as was established in this thesis.

Lastly, I would like to discuss the possible continuation of this study. The most logical step would be generalization of ACD models, for example GAS framework can be used. A study about seasonality of the dataset would also help estimate a more accurate model.

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