HIGH-SPEED TECHNOLOGY TRADING INNOVATIONS AND CAPITAL MARKET PERFORMANCE IN BULGARIA[1]

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Abstract

The paper analyses the effects of technology-based innovative techniques on Bulgarian capital market -algorithmic trading, in general, and high frequency trading (HFT), in particular - from macroeconomic costs-benefits perspective. Overwhelmingly, empirical studies emphasize that HFT improves the quality of financial markets in terms of increased liquidity, lowered transaction costs and fast price discovery. On the other side, HFT can have potential destabilizing effects, especially on emerging markets, which require increased regulation. Against this background, the European Union (EU) has introduced new regulatory measures targeting HFT, in 2018, which require fast adaptation of all market participants. Empirically, the author argues that there is a relationship between HFT, increased market volatility, fall in trading activity, liquidity and market capitalization on the Bulgarian capital market following the global financial crisis, concluding that the reasons for the fall in capital market activity are not only purely economic. Last, it elaborates on prospective implications for the Bulgarian capital market after the implementation of the new EU regulation targeting HFT.

Keywords: algorithmic trading, liquidity, volatility, market capitalization, systemic risk, EU integration

JEL Classification: G12, G19, G23

1. Introduction

Technology-based innovative techniques may have an exorbitant impact on capital markets dynamics due to increased

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interdependencies among the various segments of these markets in terms of correlations among traded financial instruments. Various empirical studies (Sornette et al., 2011) point to the potential of HFT to provoke capital market bubbles and flash crashes. According to current analyses, HFT accounts for over 77% of transactions in the UK and to about 50% - 70% of all trading in US equity markets (SEC, 2010; Kirchner, 2015; TABB Group, 2009). For Europe, HFT accounts from 24% to 43% of equities trading volume and from 58% to 76% of overall number of orders (ESMA, 2014). HFT involves processing large volume of market data in a very short time horizon (i.e. measured in milliseconds), in order to identify patterns for future price changes and derive profitable opportunities by submitting, modifying, cancelling market trade orders in less than 7 microseconds. HFT is a subset of algorithmic trading using IT programs to execute high velocity trading activity through trade execution mechanism, identifying the best time, venue and order size (Kirchner, 2015).

HFT can run counter to the existing traditional Fama (1970) approach to efficient financial markets and according to Grossman & Stiglitz (1980) there is inherent contradiction in the strong-form efficiency that no investors could have monopolistic access to stock price information to predict price movements. HFT is a form of arbitrage (i.e. variations of statistical arbitrage, Khandani & Lo, 2007). It aims to generate short-term profits based on high-speed processing of large massifs of publicly available data (about large numbers of liquid shares of stock traded simultaneously at different trading venues) and IT infrastructure innovations (complex algorithms, machine learning etc.), and to generate numerous orders which can be cancelled shortly afterwards and end the trading day on possibly flat positions to avoid commitment of capital and portfolio risks (Jovanovic & Menkveld, 2012). Thus, HFT can potentially lead to generation of a huge volume of orders at high cancellation rates (reaching 90 % or even more).

According to Government Office for Science (2011), HFT is differentiated from arbitrage strategies in that the latter principally aim to contain or hedge risks. HFT generally involves a mixture of speculative strategies (i.e. passive market making, structural, directional, statistical, cross-venue, instrument arbitrage; latency arbitrage, liquidity detection, cross-assets, cross-markets, rebate driven strategies etc.), without taking into consideration fundamental reasons for changes in stock prices but looking at arbitrage price discrepancies instead.

2. Methodology and data

The integration of the Bulgarian capital market into the EU supports the optimal allocation of capital and is of utmost importance for increasing the economic growth and competitiveness of the country. This process is a result of the joint action of institutional structures and market participants and requires further action by all stakeholders to overcome the limitations to Bulgaria's capital market in the integration process. The Bulgarian capital market remains small in size and insufficiently integrated into EU capital markets – a “periphery market” - after 10 years of fully-fledged membership, against the backdrop of consolidation processes on EU stock exchanges. Driving factors behind these processes are the need to diversify stock exchange revenues to mitigate the risks of the global financial and economic crisis and the subsequent debt crisis in the Eurozone.

The market capitalization on the Bulgarian stock exchange marked an upward trend in the period 2004-2007, before the global financial crisis has started (GFC) (Table 1, Appendix).

As Table 1 shows, the capital market is an alternative financial intermediation channel, with the market capitalization to GDP ratio reaching around 50% (according to BSE) in 2007. After this period there was a decline in market capitalization/GDP in the course of the effects of the financial and economic crisis and the withdrawal of foreign investors from the capital market of the country. Since the global financial crisis has started, market capitalization as a share of GDP continued to decline, reaching 10.89% of GDP by 2016 and then rising up to 24.08 % in 2017, but remains very low as compared to Eurozone countries (an average of 64.41% in 2016), according to ECB (2016). In empirical studies, the capitalization rate is seen as a measure of stock market development (Levine and Zervos, 1998). Low liquidity is a major flaw of the capital market in Bulgaria (Table 2, Appendix). The main factors that have negatively affected the liquidity refer to the small volume of freely traded shares (free float), the outflow of foreign investors from the Bulgarian capital market in the course of the financial and economic crisis and the deteriorating institutional and business environment with high level of corruption.

The total number of issues of financial instruments in the markets of BSE reported a decrease over the years: 557 (2008), 555 (2009), 528 (2010), 507 (2011); 496 (2012); 495 (2013) and 425, (2016) and 419 in 2017. Due to the combination of institutional weaknesses and poorly developed business environment, a number of large Bulgarian companies chose to list their securities abroad, mainly on the Warsaw stock exchange. Since 2008, the activity of investment intermediaries has decreased, analysed by number of concluded deals and realized turnover. It is related to the ongoing financial and economic crisis, the lack of liquidity on the capital market and the absence of diversified financial instruments. Moreover, in 2017, the number of stock exchange members decreased to 47, of which 5 are foreign entities. The global financial and economic crisis had a negative impact on the Bulgarian economy. In 2007, foreign investors owned 42% of the securities traded on the Bulgarian stock exchange, while after 2008 their share dropped to less than 15%. Restricted access to finance led to shrinking investment activity in almost all sectors of the economy, with gross capital formation falling by over 23.2%. Thus, the Bulgarian capital market is becoming a risk element of global financial markets. The restrictive monetary and credit policy under the terms of currency board created conditions for dependence of the investment process on external capital flows.

The paper has a twofold objective. The first one is to analyse the effect of HFT activity on the Bulgarian stock exchange for the period 2000-2017. Second, to prove empirically that the reasons for the falling stock market capitalization, deteriorating liquidity, squeezed trading volumes and increased volatility are not all purely economic, but can partially be explained by institutional weaknesses and technological advancements.

Theoretically HFT can be measured by proxies of trading activity as:

1) stock-based approach as statistics on large volumes of order placements and cancellations, order to trade ratio (Brogaard et al., 2014; ESMA 2014) providing upper bound on HFT activity. In USA high order to trade ratios are proxy for HFT activity (or message traffic activity). According to ESMA estimations (2014) in EU the median unweighted order to trade ratio is 18, 1st quartile is around 3 and 3rd quartile is about 64. Thus if 10% of order modifications and cancellations in any stock are faster than 100 ms, the trading activity

is classified as HFT by ESMA report (2014). Under this approach ESMA has established that the median HFT activity in EU ranges between 31 % and 52 %.

2) direct (or institution-based) approach based on identification (flagging) of HFT firms (ESMA, 2014) providing lower bound on HFT activity. ESMA (2014) has established that under this approach HFT accounts for 21 % to 30 % on 9 EU stock exchanges.

3) collocation is a proxy for HFT activity and according to ESMA estimations (2014) it accounts for about 75 % of value traded in EU. Using the advantages of co-location and physical proximity in direct data feed Menkveld (2012) defines HF traders as “modern market makers” who are generally gaining millisecond speed advantages from co-location.

Following the methodology of Laube et al. (2013) the introduction of the electronic trading platform Xetra in 2008 on the Bulgarian stock exchange is used as an exogenous market structure change (instrumental variable) to identify HFT activity because it is particularly designed to respond to the needs of HFT. Main indicator of HFT activity is putatively increased electronic messages flow for 2008 onwards after the introduction of the electronic trading platform Xetra. However, this direct indicator of HFT is unobtainable for the Bulgarian capital market because it cannot be publicly accessible. For that reason, the present research uses the following proxies for HFT:

Firstly, HFT based on the per cent of shares held by institutional investors in total trading volume. The database from OECD (2017) shows the following institutional statistics for assets (in %) held by institutional investors:

Table 3

Financial assets as % held by institutional investors

	2009	2010	2011	2012	2013	2014	2015	2016
Czech Republic	3,8	4,2	3,7	4,1	4,6	5	5,3	6,7
Greece	3,7	3	2,1	2,5	2,8	2,7	2,4	2,3
Hungary	11,4	13,8	11	11,5	14,7	16,5	16,3	15,8
Slovenia	6,2	6,3	4,9	5,1	5,1	5,7	6	6,1
USA	85,8	89,3	86,1	94,4	105,8	108,2	103	106,3

Source: author’s compilations based on OECD Institutional Statistics, 2017

The Bulgarian supervisory authority, however, does not collect and store information about the share of institutional investors holdings in total outstanding shares and trading volume, so the estimations have been based on the average values for Central and Eastern Europe EU member states above (Table 3). During the period 2000 – 2017 the per cent of HFT on the Bulgarian stock exchange could be estimated to vary from the lowest 57,5 % (2007) to the highest 96 % (2012). For estimations purposes, the analysis is based on empirical findings of Zhang (2010) who is calculating HFT using the following formula:

HFT = Total Turnover – (Total Turnover x per cent of institutional holdings in shares outstanding+ Total Turnover x per cent of retail holdings in shares outstanding) (1)

Since the retail investors on the Bulgarian stock exchange are holding negligible share in total shares outstanding, only institutional holdings data, averaged on the data from OECD for CEE EU member countries has been used.

Secondly, HFT based on ESMA approximations (ESMA, 2014): ESMA empirical analyses show that HFT accounts for 24 % of value traded (HFT flag approach) to 43 % of the lifetime of orders (or order to trade ratio) approach as stock based measure. For the number of trades corresponding HFT activity is estimated between 30% and 49% and for number of orders between 58% and 76%.

Thirdly, HFT based on collocation: from the total sample of 43 stock exchange members in 2017, 17 members have head offices located within 1 mile (1,6 km) from the building of the Bulgarian Stock Exchange. Thus, potentially these intermediaries on the stock exchange could have been presumed to engage in HFT. Due to the very wide variation in prospective HFT contained in proxies 1) to 2) above, in the present research has employed HFT approach based on collocation. This approach is based on ESMA theoretical and empirical results (2014), where most HFT activity (within the sample of 100 stocks from 9 EU countries) has been found to be linked to market participants using collocation services. According to Gomber et al. (2015) using direct market access registered stock exchange members may use various discount fees (asymmetric pricing schemes) to generate trading volume and incentivize liquidity provision. For Allen (2016) profit-driven exchanges do not prioritize the regular and traditional long-term investors but traders as HFT generating higher trading volumes and paying for preferential access via co-location, thus implicitly harming retail investors who do not have this privileged access. This creates the problem of conflict of interest (Arnuk & Saluzz, 2012): stock exchanges have the incentive to sell preferential access to generate additional profits from collocation fees but they also have obligations to provide equitable and fair access to all market participants on the trading venue. The annual turnover of these 17 member intermediaries on BSE has been estimated on average to represent around 77 % of the turnover of all stock exchange intermediaries for the period 2008-2017 in Bulgaria and the equation (1) has been corrected as follows in order to arrive at approximate HFT based on trade value:

HFT = Total Turnover – (Total Turnover x % of institutional holdings) (Total Turnover x per cent of non-proximity stock exchange member holdings) (2)

The methodological estimations of HFT on the Bulgarian capital market require as a first step the application of logit regression method which is a type of probabilistic statistical classification model. The dependent variable is categorical binary variable for HFT (in which 1 is “there is HFT activity” and 0 is “lack of HFT activity” on the Bulgarian capital market). The independent variable X is “the distance in km from the stock exchange” calculated in ln. The aim is to test how distance in km (i.e. collocation) affects HFT.

2. Empirical Results about High Frequency Trading and Stock Market Performance in Bulgaria

The main results from the logit regressions indicate the following:

Table 4

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	,000[a]	,728	1,000
a. Estimation terminated at iteration number 18 because a perfect fit is detected. This solution is not unique.			

Source: author’s calculations

From Table 4, which presents the Cox & Snell R Square and the Nagelkerke R Square as methods of calculating the explained variation (also referred to as “pseudo R^2”), it is clear that the values indicate that the explained variation in the dependent variable Y "HFT incidence" based on the logit regression model range from 0,728 to 1. The likelihood ratio of 0,000 is a proof of the goodness-of-fit statistics of the model, similar to Pearson's chi-square presented below.

Table 5

Classification Table[a,b]

Observed			Predicted		
			HFT		Percentage Correct
			No Collocation	Collocation	
Step 0	HFT	No Collocation	27	0	100,0
		Collocation	15	0	,0
	Overall Percentage				64,3

a. Constant is included in the model.

b. The cut value is .500

Source: author's own calculations

From Table 5 it is obvious that the "cut value" is 0,500, meaning that if the probability of a case being classified into the "Collocation" category is greater than 0,500, then that particular case is classified in the "HFT incidence" (Yes = 1) category. The overall correct percentage of predicted probability of Collocation is 64,3 % and in that case the estimated probability of HFT occurring (taking place) based on collocation is 64,3 % (> than the cut value 0,500), classifying the event HFT as likely to take place or to occur.

Table 6

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-0.588	0,322	3,332	1	0.068	0.556

Source: author's own calculations

From table 6 above, the Wald statistics which is used to determine the statistical significance of the independent variable "Collocation", which is 0.068 (>0.05) and indicates that the independent variable does not add significantly to the model. The odds of having HFT incidence is 0,556 (Exp(B)) greater with decrease in physical proximity of stock exchange intermediary head office by 1 km to the stock exchange building.

Converting odds to probabilities:

Y est. = ODDS/ (1+ODDS) = 0.556/ (1.556) = 0.3573, or 36 % probability of having HFT incidence with decrease in physical proximity of stock exchange member to the stock exchange.

Table 7

Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step 1 Step	54,748	39	0.048
Block	54,748	39	0.048
Model	54,748	39	0.048
Hosmer and Lemeshow test	0.000	1	1.000

Source: author's own calculations

The logit regression was performed to ascertain the effect of collocation (or "physical proximity") of stock exchange intermediaries to the stock exchange on HFT incidence on the Bulgarian capital market. The logistic regression model is statistically significant (Table 7 above), since χ^2 is 54,748, with Sig. 0.048 < α = 0.05. The logit regression model explains 100 % (Nagelkerge R^2) of the variance in HFT incidence and correctly classifies 64,3 % of the cases of collocation. Thus 1 km in physical proximity of stock exchange intermediary premises to the stock exchange leads to 0.556 greater probability of HFT incidence associated with it, although it is not statistically significant (Sig. =0.068 > α = 0.05). The Hosmer and Lemeshow goodness of fit test statistics has Sig. 1> 0.05 and we cannot reject the null hypothesis that there is no difference between the observed and model-predicted values of the depended variable. The model does not predict values significantly different from the observed values.

Overall, the logit regression model described above can be concluded to be valid, because it has observed the four assumptions for validity of results:

1) the dependent variable "HFT incidence" is measured on a dichotomous scale (presence "1" or lack "0" of HFT).

2) the independent variable is "collocation" and it is a continuous variable for distance in km from stock exchange members' premises to stock exchange building. In the sample of 43

intermediaries, 17 are located within 1 mile (1,6 km.) from the stock exchange.

3) the analysis is based on independence of observations and the dependent variable "HFT incidence" has mutually exclusive and exhaustive categories.

4) linearity of the relationship between the continuous independent variable and the logit transformation of the dependent variable has been proved as follows:

The applied **Jarque-Bera test** as a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution shows the following statistics: for HFT incidence variable Jarque-Bera p =0.0258974 < α = 0.05). For Collocation variable the Jarque-Bera p = 0.232821 which is an indication for divergence from the normality criterion. In order to test whether this departure from the assumption of normality is moderate, log-linear regression model has been applied. The results are as follows:

Table 8

Correlations

	HFT Incidence	Collocation in km
Pearson Correlation HFT	1,000	-0.786
Pearson Correlation Collocation in km	-0.786	1,000

Source: own calculations

From Table 8 above, the negative correlation coefficient between HFT and collocation of -0.786, indicates significant negative relationship, shows that the increase in distance expressed in km leads to decrease of the HFT incidence and vice versa, the decrease in physical proximity in km leads to increase in HFT incidence.

Table 9

ANOVA

Model	Sum of squares	df	F	Sig.(p value)
Regression	5,955	1	69,19851	2,43e-10
Residual	3,688	40		
Total	9,643	41		

Source: own calculations

Table 9 above shows that the Ordinary Least Square Model estimating the dependence between HFT and collocation in km is adequate, since Sig. = 0.000 < α = 0,05).

Table 10

Coefficients

Model	Unstandardized coefficients		t	Sig.
	B	Standard error		
Constant	0,777352	0,0670340	11,60	1,60e-014***
Collocation in km	-0,438724	0,0527404	-8,319	2,43e-010***

Source: own calculations

From Table 10 above it is clear that Sig.2,43e-010, the t-test is robust and not sensitive to moderate departures from the assumption of normality. Since the sample size is large enough (the number of tested stock exchange intermediaries is 43 > 30 observations), then we can conclude that the fourth requirement for linearity has been met.

The co-integration regression model of the relationship between "HFT incidence" and "Collocation" in km. shows the following results:

Table 11

Engle-Granger Cointegration regressions with dependent variable HFT incidence (1st lagged order with constant and trend)

	coefficient	standard error	t-statistics	p-value
Constant	1,05500	0,0724416	14,56	1,39e-017***
Collocation in km.	-0,224901	0,0564000	-3,988	0,0003***
time	-0,0215983	0,00396791	-5,443	2,86e-06

Source: own calculations

Unit root test in HFT(1-st differences) incidence variable: asymptotic p-value 0,0005009<α = 0,05. Accept stationarity or unit root.

Unit root test in Collocation variable (1-st differences): asymptotic p-value 0,00001 < α = 0,05. Accept -stationarity

The unit root test in the residuals around the estimated values of the tested variables (augmented Dicky Fuller test) shows the following asymptotic p-value of 0,04711< α = 0,05. → Accept stationarity in the residuals. The co-integration coefficient of determination is R^2= 0,786264 and $R^2_{adj.}$ = 0,775577.

From Table 11 above, the regression is as follows:

$$\textit{HFT incidence} = 1{,}005500 + (-0{,}224901)\ \textit{Collocation in km} + (-0{,}0215983)\ \textit{time} \quad (3)$$

It can be concluded that the influence of the parameters in front of the Constant, “Collocation in km” and “Time” are significant at 5 % level of significance and that there is co-integration among the two variable series “HFT incidence” and “Collocation in km”.

The application of the Engle-Granger co-integration test only with constant, constant and trend, and without constant and trend leads to the conclusion: acceptance of the null hypothesis of stationarity in the two variables and the residuals of the co-integration regression. The evaluated variables are co-integrated.

As a second estimation technique, a linear regression model (OLS) has been employed to test for linear relationship between the independent variable HFT and the variables: liquidity ratio, market capitalization to GDP ratio and volatility ratio. The application of Engle-Granger co-integration regressions goes through the following algorithm:

- testing for stationarity for each of the variables (dependent and independent ones) using the Augmented Dickey-Fuller criterion and the following equation:

$$Y_t = a_0 + a_1 * x_t + e_t \quad (4)$$

- estimating the parameters of the econometric model by using the Least Squares method.

-estimating the residuals around the estimated values of the variables using the formula:

$$e_t = y_t - \breve{y}_t \quad (5)$$

- testing for zero hypothesis of stationarity among the residuals of the variables using the following formula:

$$e_t = \theta * e_{t-1} + u_t \quad (6)$$

The application of the above outlined algorithm leads to the following results:

A. Unit Root test (Dicky – Fuller test) results:

Table 12

Unit root test estimations for stationarity

Market capitalization ratio	HFT	Liquidity Ratio	Volatility Ratio
Unit root test first differences second lag order: asymptotic p-value 0,002371< α = 0,05. Accept stationarity.	Unit root test first differences second lag order: asymptotic p-value 0,005009< α = 0,05. Accept of stationarity.	Unit root test first differences second lag order: asymptotic p-value 1.396e-19< α = 0,05. Accept stationarity.	Unit root test first differences second lag order: asymptotic p-value 0,0004551< α = 0,05. Accept stationarity.

Source: own calculations

B. Least Square regression test estimations

Table 13

Regressions with dependent variable Market capitalization ratio (2^{nd} lagged order)

	coefficient	standard error	t-statistics	p-value
Constant	3,73921	1,83563	2,037	0,0610 *
HFT (first differences)	−0,793249	0,171362	−4,629	0,0004 ***
R^2 = 0,604836 $R^2_{adj.}$ = 0,576610 F (1,14) 21,42832 P – value (F) 0,000390				

Source: own calculations

As Table 13 indicates, the coefficient of determination is R^2= 0,604836 and its alternative adjusted value $R^2_{adj.}$ = 0,576610 show that the model explains about 60 % in the variation of the dependent variable market capitalization with changes in the independent variable HFT. The model indicates negative relationship between the variables – thus 1 % increase in HFT leads to 0.7932% decrease in market capitalization ratio, all else held constant. The t-test Sig.= 0.0004 is indicative of statistical significance of the regression model. The Least Square Model estimating the dependence between Market capitalization ratio and HFT is adequate (F – test), since p = 0,000390 < α = 0,05. Theoretically ESMA (2014) has established from a study of 9 EU countries that level of HFT activity increases with the market capitalization of stocks. Here the results are indicative of underdevelopment of the Bulgarian capital market and the negative consequences of HFT on it.

Table 14
Regressions with dependent variable Volatility ratio (3rd lagged order)

	coefficient	standard error	t-statistics	p-value
Constant	−3,96878	2,86823	−1,384	0,1881
HFT (first differences)	0,701955	0,267758	2,622	0,0201**
R^2 = 0,32927 $R^2_{adj.}$ = 0,281361 F (1,14) 6,872782 P – value (F) 0,020113				

Source: own calculations

According to Table 14, the coefficient of determination is R^2= 0,32927 and its alternative adjusted value $R^2_{adj.}$ = 0,281361 show that the model explains about 30 % in the variation of the dependent variable volatility ratio with changes in the independent variable HFT. The model indicates positive relationship between the variables – thus 1 % increase in HFT leads to 0.7019% rise in volatility ratio, all else held constant. This is in line with empirical findings of Zhang (2010) who also established that this positive correlation appears to be specifically pronounced under conditions of market uncertainty. Other studies that point to increased volatility due to HFT after 2005 are: Boehmer et al. (2015); Benos & Segade (2012), Caivano (2015), Jarrow and Protter, 2011. The t-test Sig.= 0.0201 is indicative of statistical significance of the regression model. The Least Square Model estimating the dependence between volatility ratio and HFT is adequate, since p value is 0,020113 $< \alpha = 0,05$).

Table 15
Regressions with dependent variable Liquidity ratio (2nd lagged order)

	coefficient	standard error	t-statistics	Sig.(p-value)
Constant	53,146	4,067	13,068	0,000
HFT (first differences)	-0.572	0,073	-7,793	0,000
R^2 = 0,890 $R^2_{adj.}$ = 0,778 F (1,16) 60,727 P – value (F) 0,007				

Source: own calculations

As per Table 15 above, the coefficient of determination is R^2= 0.890 and its alternative adjusted value $R^2_{adj.}$ = 0,778 show that the model explains over 80 % in the variation of the dependent variable liquidity ratio with changes in the independent variable HFT. The model indicates negative relationship between the variables – thus 1 % increase in HFT leads to 0.572 % decrease in liquidity ratio, all else held constant. The t-test Sig.= 0.000 is indicative of statistical significance of the regression model. The Least Square Model estimating the dependence between volatility ratio and HFT (F - test) is adequate, since p - value is 0,007 $< \alpha = 0,05$. These results are in line with the findings of Chaboud et al. (2011) which point to HFT and its negative impact on liquidity especially in turbulent times and through cross-sectional correlations among markets. Also Brogaard et al. (2015) have found negative relationship between liquidity and HFT due to adverse selection costs of limit orders for slower traders when HF traders act as liquidity takers (especially in times of market uncertainty) This has been also confirmed by Yamamoto (2015).

Table 16

Co-integration regressions with dependent variable HFT (2nd lagged order)

	coefficient	standard error	t-statistics	p-value
constant	0,306667	0,674887	0.4544	0.6565
Dummy variable for 2008 (introduction of Xtera)	41,3933	2,69955	15.33	3,80e-010***
R^2 = 0.943801 $R^2_{adj.}$ = 0.939787 F (1,16) 60,727 P – value (F) 0,007				

Source: author's estimations

Table 16 above shows that the coefficient of determination is R^2= 0.943801 and its alternative adjusted value $R^2_{adj.}$ = 0.939787 show that the model explains about 94% in the variation of the dependent variable HFT with changes in the independent dummy variable. The model indicates positive relationship between the variables – thus the introduction of Xetra in 2008 on the Bulgarian stock exchange led to rise in HFT by about 41,39 %, all else held constant. This is consistent with the findings of Laube et al. (2013) who found that the introduction of Chi-X MTF in European stock markets increased the number of messages by an average of 31,346 messages per day due to this exogenous stock market change and the effect is more pronounced for large volume stocks. Thus introduction of Xetra on the Bulgarian capital market can serve as a reliable exogenous proxy for the identification of HFT activity. The t-test Sig.= 3,80e-010 is indicative of statistical significance of the regression model. The Least Square Model estimating the dependence between HFT and dummy variable for 2008 (the implementation of the electronic trading platform Xetra) is adequate, since p - value is 3,80e-10 < α = 0,05).

C. Correlation estimations among tested variables is as follows:

Table 17

Correlations Matrix (Pearson Correlation, Sig. 2-tailed)

	Liquidity Ratio	**Volatility Ratio**	**Market Capitalization Ratio**	**HFT**
Liquidity Ratio	1	0.617** (Sig. 0.006) VIF stat = 1	-0.250 (Sig. 0.318) VIF stat = 1.06	-0.890** (Sig. 0.000) VIF stat = 4.784
Volatility Ratio	0.617** (Sig.0.006)	1	-0.433 (Sig. 0.073)	-0.380 (Sig. 0.119)
Market Capitalization Ratio	-0.250 (Sig. 0.318)	-0.433 (Sig. 0.073) VIF stat.= 1.000	1	0.011 (Sig.0.965)
HFT	-0.890** (Sig. 0.000)	-0.380 (sig. 0.119)	0.011 (Sig. 0.965)	1

Source: author's estimations

From Table 17 above it can be concluded strong negative correlation is exhibited between HFT and liquidity ratio, which is statistically significant (Sig. 0.000 < α = 0.05). The VIX statistics does not denote presence of statistically significant collinearity between the tested variables.

3. Macroeconomic Consequences of Technology-Based Innovative Techniques

3.1 Macroeconomic and Social Welfare Gains

The traditional academic literature on HFT has identified the following macroeconomic and social welfare gains from HFT so far:

A. HFT reduces transaction costs and boosts price discovery

Proponents of HFT generally emphasize the potential of HFT to boost liquidity on stock markets with concomitant positive effects on transaction costs reduction and increased price discovery (Hendershott & Riordan, 2009; Hendershot, Jones and Menkveld, 2010; Menkveld, 2011) on liquid and deep markets as NYSE and Nasdaq based on increased variance ratios as a causal effect of algorithmic trading due to increased information getting into prices and reducing the noise (errors or transitory component) in prices, which is consistent with theoretical models of informed trading (Kyle, 1985).

Specifically, for the capital market performance in Bulgaria, it can be concluded that this positive effect has not been realized. HFT is associated with fall in liquidity ratio (see table 15) and deterioration in the price discovery process.

B. HFT improves market quality (measured by volume, spread, volatility, price efficiency)

The mechanism for improved market quality has been theoretically described as follows: the increased liquidity (Soronette & von der Becke, 2011) boosts trading volumes, narrows bid-ask spreads, and thus reduce stock price volatility (Brogaard, 2011; Hasbrouck & Saar, 2012). The positive externalities from this process are: increased social value of information through price discovery and efficiency (Kirchner, 2015; Brogaard et al., 2012; Handershott & Moulton, 2011)). Aitken et al. (2012) established positive effect of HFT on market efficiency based on reduced costs of trading and synchronization of price movements (Conradt, 2011). According to a study by Deutsche Bundesbank (2016) HFT in normal times supply liquidity close to the best bid-ask price consistent with market making strategy. According to research by Gider et al. (2015) price efficiency is generally higher on large stock exchanges with high levels of market capitalization. HFT reduces price efficiency as market prices incorporate less information based on company fundamentals.

Regarding the Bulgarian capital market, the fact that HFT is associated negatively with market liquidity, it has led to falling trading volumes and increased stock price volatility (Tables 13, 14, 15) with resultant fall in market capitalization levels following the introduction of the electronic trading platform Xetra in 2008 (as an instrumental proxy for HFT). It can be concluded that for the small and inherently underdeveloped Bulgarian capital market, the consequences from HFT have been generally in the direction of deterioration of market quality.

C. HFT leads to higher returns to investors →lowers cost of capital

The decreasing transaction costs raise asset returns to investors and thus to increased asset prices, which in turn positively influences investors' wealth and social welfare (Kirchner, 2015). In broad macroeconomic aspect the higher asset prices lower the cost of capital for companies and incentivize them to undertake larger investments. This in turn boosts productivity levels, with subsequent rise in wages and living standards.

For the Bulgarian capital market, obviously the fall in market liquidity, increase in market volatility and drop in market capitalization ratio have impacted on the reverse the returns of traditional long-term investors (especially institutional and retail investors) with negative consequences for social welfare.

3.2. Macroeconomic and Social Welfare Losses

A. HFT accelerates market dynamics such as bubbles and flash crashes

There is empirical stock market evidence (Haldane, 2011) that the flash crash in 2010 on E-market S&P futures market segment in US has been partially explained by HFT (Commodity Futures Trading Commission report, SEC, 2014). This points to the fact that such market disruptions generally affect most liquid and deep markets as a result of herding behaviour, and the Bulgarian capital market can still be described as underdeveloped and mostly illiquid.

B. Minimal liquidity welfare gains derived from HFT and largely negative on a long-term investment horizon

Empirical evidence suggests that the welfare gains from HFT on liquidity may well be overestimated in long-term periods (Sornette et al., 2011). The potential for increased liquidity to generate volatility bursts (i.e. flash crashes, bubbles etc..) and overall market risks and disruptions is due to possible spillover effects to other market segments instigated by collective herding behaviour. According to Wyman (2012) HFT provide "ephemeral" or "false" (Lewis, 2014;

Patterson, 2012) liquidity which is drained in times of market stress. Some estimations of Allen (2016) point that if the trend with HFT continues, the traditional long-term investors will leave the market. As a reaction, in US in 2015 Investors' exchange was set up in view of the unfair advantages on other trading venues. The expectations are this measure will contribute to enhancing the quality of US equity markets. To preserve liquidity Harris (1994) suggests information on quotes to be only released when markets are closed or at pre-announced times. For Allen (2016) the best way to prevent HFT monopolizing the trading venues is the use of randomizer: regulations to delay each order between 0 to 10 milliseconds and mitigate the problem of front-running. Another possible approach to combat rent seeking behaviour of HFT is to report approximate order sizes or aggregated volumes at different intervals.

For the Bulgarian capital market this theoretical explanation of HFT has been explicitly proven. The implementation of Xetra in 2008 coincided with the start of the GFC and the existing market volatility was further reinforced by HFT leading to subsequent fall in liquidity levels and rising market risks for other traditional market participants, driving some of them out of the market.

C. Positive correlation between HFT and stock price volatility→negative impact on financial stability and lead to non-linear financial system with possible systematic risk effects

A strong positive correlation between HFT and stock price volatility has been documented by Zhang (2010), especially for stocks with highest market capitalization. The question is about the causality of the relationship: for Linton et al. (2018) higher volatility in the aftermath of the GFC caused higher activity of HFT offering profitable trading opportunities. HFT negatively impacts on price discovery due to overreaction of stock prices to two sources of public information: macroeconomic news announcements (Jegadeesh et al. 1993) and imbalances in the limit order book (Cao et al, 2009). Generally, HFT can lead to reduced volatility at the level of individual stocks but may intensify tail risks and lead to aggravated volatility at macroeconomic level (Kirilienko, Kyle, Samadi & Tuzun, 2011). This is due to the fact that generally HF traders go in opposite direction of orders of institutional investors and attract herding behaviour. This in turn deteriorates the operation of the long-term price discovery mechanism with negative consequences for market confidence and leads to qualitatively different and non-linear financial system (Glosten, Milgrom, 1985). According to Laube et al. (2013) HF traders lead to increased cross and intra-market correlations of returns and this may be associated with extreme systemic events.

For the Bulgarian capital market and its performance, the empirical results proved the positive correlation between HFT and stock market volatility (see Table 14) with negative consequences on the price discovery mechanism and further fall in market capitalization levels.

D. HFT may pose systemic risk

The mechanism through which HFT could endanger financial stability is that HFT potentially leads to higher levels of liquidity. But at certain point (i.e a plateau) increased liquidity generates diminishing welfare gains because of herding potential. It may threaten systemic stability through the interrelations among capital market segments (the "complex systems approach" proposed by Sornette et al., 2011) and Jiang et al. (2010); Sornette & Zhou (2006). HFT agents, being short-termists who do not absorb risks, may pose systemic consequences also due to the fact that they provide liquidity at their own discretion and do not have the obligations of traditional market makers. For Froot et al. (1992) HFT relies mainly on reduced waiting time in trades (to milliseconds or lower), short-term information and adaptive algorithms with built-in stop losses, which may lead to greater systemic risk consequences. Laube et al. (2013) identify two types of systemic risk in HFT: one is related to stock returns (and their relation to market variance) and the other – to stock liquidity and its covariance with market liquidity (and the algorithmic trading behavior of investors, Chaboud et al., 2011).

For the Bulgarian capital market and its performance this risk so far has been contained due to the following reasons: 1) small and generally underdeveloped capital market in Bulgaria. 2) lack of diversified and complex financial instruments on the market. 3) After the failure of the KTB as one of the principal proximity stock exchange intermediary in 2014, generating about 15 % of the total turnover of proximity stock exchange members, the possible systemic consequences have been contained based on the government liquidity assistance scheme of BGN 3,3 billion.

E. HFT may pose operational risk

This risk can arise in the course of stock market infrastructure disruptions (i.e. IT cyberattacks etc.) and according to Kirchner (2015) analyses machine algorithms may lead to emergence of novel and very sophisticated ways of stock market manipulations. Thus Brogaard et al. (2012) found that HFT may lead to increased transaction costs due to the need for technological IT upgrades by all stock market intermediaries (technological costs).

For the Bulgarian capital market, presently the lack of publicly disclosed information about HFT and their market strategies, the analysis of this threat from HFT needs further quantification and consideration.

F. HFT may lead to market manipulations and market abuse → with negative consequences on market trust and confidence

Critics of HFT point to some of the manipulative strategies that HFT can employ (as layering, spoofing, quote stuffing, flashing, smoking etc.) which involve placing orders without intent to trade and exploiting slower participants' reaction. Some trade protection mechanisms are associated with use of dark pools (for large block trades) and internalization of retail orders, but these may lead to higher transaction costs to retail and institutional investors. These negative consequences on financial markets efficiency will persist as long as HF traders are small minority from the investment community. Model simulations done by Vigrilio (2015) established that HFT leads to rejection of the efficient market hypothesis and confirms the consistent risk-free returns generated by HF traders at the expense of other "patient" investors. Behaving as market makers without having the proportional obligations of these market participants, HF traders realize profits without bearing sufficient risks faced by other market players thus shaking market trust and confidence (Zhang & Powell, 2011). A study by Brigida (2016) found that only those HFT trading in the first 50 milliseconds after the release of stock market gas storage report in US realized significant profits proving that HFT avails trades in high speeds but the tests did not find evidence on informed trading (i.e. positive correlation of HFT with public information announcements, Brogaard et al (2013).

For the Bulgarian capital market, lack of public information prevents analysis of abusive or manipulative strategies of HFT. Yet, the fact that HFT is negatively associated with liquidity and market capitalization and positively with market volatility, is a proof for negative impact on market trust and confidence in the Bulgarian capital market as an alternative efficient source for firm financing after 2008.

G. HFT leads to inequality of opportunity → disincentives to invest in the market

Even in well-regulated stock markets HFT may lead to unequal outcomes for trading participants due to the information advantage of HF traders. Yet the application of too restrictive regulation as financial transaction tax may discourage market participants and induce capital outflow. The financial transaction tax burden is usually shifted from stock intermediaries on end-investors and the final outcome is increased transaction costs (Matheson, 2010), reducing market liquidity (due to inverse relation between transaction costs and trading volume), lowering the rate of return and of asset prices. Another aspect of inequality among traders is the adverse selection costs that HF traders impose due to their information and speed advantage. The TABB Group (2012) has established that HFT sector generated about 800 USD of profits in 2008 and this exorbitant amount of rents potentially impacts on retail and institutional investors. One important indicator in this respect is to monitor the stock prices of intermediaries and whether they exhibit any extreme profitability patterns.

In conclusion, the established privilege of co-location for this group of stock market members deepens the gap between market participants, discriminates traditional long-term investors and discourages their participation on the Bulgarian stock market. Based on the theoretical review of existing academic literature on HFT it can be concluded that the short-term static costs – benefits should be juxtaposed against long-term dynamic costs-gains in order to arrive at the net social gains or losses derived from HFT on stock market performance.

3.3 Regulatory initiatives at EU level targeting HFT and potential consequences for capital markets

Regulations and various tax measures are considered the main instrument to mitigate the broadly negative welfare gains from HFT. One such approach is the coordination of data on HFT across assets and markets to better measure and evaluate the impact of HFT on stock market performance. The main market tools to contain sharp and short term movements in prices (defined as flash crashes or rallies) have been use of market trading curbs and circuit breakers. According to Bell & Searles (2015) the approach at EU level is generally in the direction of suppressing HFT through fees and increased regulation. Imposition of cancellation fees on orders (according to Yamamoto, 2015) discourages HF traders to place limit orders and motivates them to execute market orders, thus causing wider spreads and higher stock volatility. Due to the significant welfare losses and the impossibility to differentiate the net effect of HFT presently, at EU level the approach is aimed the middle way: not prohibiting explicitly HFT but subjecting it and other forms of AT to specific supervision (Recital 59, MiFID II) according to Busch (2016). This requires enforcing stricter regulation and disclose regime for HFT as subset of algorithmic trading with the implementation of Markets in Financial Instruments Directive II MiFID II) and Markets in Finacial Instruments Regulation (MiFIR in January 2018.The rules addressing the systemic risks for financial stability derived from HFT require from HFT firms, investment firms, operators of trading venues to upgrade their systems, processes and controls to counter the new technology-generated risks with the growth in HFT activities.

The new regulatory regime for AT and HFT imposes on investment firms, engaging in this types of activities implementation of risk controls (compliance with market abuse regulations; application of business continuity arrangements, risk policies; operational safeguards etc.), recording of all placed, executed orders, cancellations and quotes and disclosure to competent authorities. The trading venues of activities of HFT firms have the discretion to impose higher cancellation fees on those market participants exhibiting high ratio of cancelled to executed orders or engaging in HFT. These investment firms need authorization and demonstrate they meet the authorization requirements and provide accurate and timely information to the competent regulatory authorities. The new regulatory measures require from HFT firms change in their business model to contain possible risks arising from their activities. According to MiFID high message intraday rate of orders, quotes, cancellation is defined as at least two messages per second with respect to single financial instrument, or four messages per second for all financial instruments traded on a given trading venue. The messages relate only to proprietary trading on own account by the HFT firms and not on behalf of clients.

The existing EU market abuse regulations explicitly prohibit spoofing and other strategies that potentially may be employed by HFT firms not intended to execute transactions but to disrupt orderly function of the markets though overloading and stuffing trading systems with large volume of orders. The trading venue may indicate by flagging the orders generated by algorithmic and HFT and to disclose the information to competent authorities as a reaction against potentially abusive techniques. It should be capable of handling peak volumes and to protect itself against technical failures of members' algorithms by using various volatility interruptions and circuit breakers.

The expected benefits from the stricter MiFID II regime for HFT are wider participation in regulated markets, increased liquidity, narrower spreads, reduced short-term volatility and better execution of client orders. Specifically, the risks from HFT involve potential for systems overloading and overreaction to events and macroeconomic and market news. On the downside the expectations (Deloitte, 2016) are that the implementations of the reform package will lead to further squeeze of liquidity. ESMA is expected to further judge the need for striking the right balance between increased transparency, disclosure and monitoring and stock market liquidity. The new rules require from trading venues to establish limits to the ratio of unexecuted orders to transactions and this will obviously lead to further drain of liquidity on stock markets. To counter this, MiFID II rules require the firms engaging in HFT to execute market making during a specified period of the trading day thus leading to predictability and continuous liquidity supply. The main risk from HFT remains the loss of market trust and confidence so the regulations in MiFID require further supervision and transparency, open communication to guarantee fair and non-discriminatory access and maintain confidence of all market participants.

4. Future research directions

One possible strand of future research points to analyzing HFT and its effects on systematic risk in financial markets through better understanding of the interaction of different trading methods (high versus low frequency trading; fundamental versus technical trading), financial instruments (stocks, options, ETFs, futures contracts etc.) and markets (equities, forex, commodities.). These effects may best be analysed by application of complex systems approach (accounting for the non-linearity of financial markets, Hommes & Wagener, 2009; Evstigneev, Hens & Schenk-Hoppe, 2009), agent-based models established on behavioural patterns (i.e. collective herding regimes) and agent heterogeneity in the formation of expectations (Chiarela et al., 2009). Using interdisciplinary approach (financial economics, behavioural finance, statistical physics et.) could potentially be better tool for explaining bubble-like behavior in HFT (noise trading, herding, non-linear trend following, value investing etc., Kindelberger, 2000; Sornette, 2003; Jiang et. Al. 2009).

Another strand of future research is to empirically test and quantify the main macroeconomic costs and benefits for the Bulgarian capital market before and after the introduction of Xetra in light of the new EU regulatory framework introduced with MiFID II. Third strand of future research will be to delineate the effects the GFC and HFT on market capitalization and capital market performance in quantitative terms and to try to empirically measure what proportion of the fall in market capitalization in Bulgarian capital market was caused by GFC and by HFT separately. Yet, one final strand of future research would be to empirically test the significance of the institutional factors in stock market development in Bulgaria, and more broadly in South and Eastern Europe. Besides institutional factors, future research calls for inclusion of technological &digital factors influencing stock market development, besides AT and HFT.

5. Conclusion

The results of the econometric models on HFT and its impact on the underdeveloped Bulgarian stock market and its performance show that HFT may generally be considered as a potential source of risk due to the relatively low liquidity as a result of increased volatility of stock prices. For that reason, market regulators have to heighten prudential monitoring and supervision on all market participants in light of the newly introduced EU regulatory MiFID framework targeting HDT and its consequences on stock market performance and financial stability. The institutional factor will be crucial in this process because of the need of the regulatory body of the Bulgarian capital market not only to monitor strict application of the regulatory framework for HFT, but also to develop the required level of knowledge and expertise in analysing the various market strategies employed by HFT firms. Boosting the institutional capacity of the Financial Supervision Commission will be vital and may require increased cooperation and exchange of information with ESMA and the other regulatory authorities in the field.

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APPENDIX

Table 1

Market capitalization on BSE

Indicator	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Market capitalization (billion BGN)	4,033	8,433	15,214,	28,986	12,460	11,795	10,754	12 ,435	9, 828	9, 961	9, 756	8, 587	9, 683	23,620
Market capitalization /GDP (%)	10.54	20.11	29.30	51.29	18.73	17.21	15.22	16,13	12,71	12,54	12,39	10,19	10,89	24,08

Source: the authors, according to data from BSE, NSI, www.bse-sofia.bg, www.nsi.bg

Table 2

Liquidity Ratio and Trade Volume on BSE

Indicator	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Liquidity Ratio (%)	40	38	22	33	23	13	9	12	15	8	14	13	14	8
Trade Volume (in billion BGN)	1,596	3,182	3,384	9,640	2,903	1,551	920	1,498	1,447	2,008	1,414	1,154	1,357	1,891

Source: the authors, according to data from BSE, NSI, www.bse-sofia.bg, www.nsi.bg