Working papers

The impact of high-frequency trading on volatility

Evidence from the Italian market

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March 2015

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Commissione Nazionale per le Società e la Borsa

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ISSN 2281-3519 (online)

L'impatto del trading ad alta frequenza sulla volatilità

Evidenza empirica sul mercato italiano

*V. Caivano**

Sintesi del lavoro

Nell'ultimo decennio, il trading ad alta frequenza (HFT) ha registrato una crescente diffusione nelle Borse di tutti i principali paesi avanzati. I dati più aggiornati prodotti da uno studio ESMA indicano che in Europa il peso degli scambi riconducibili all'HFT è stimabile in media tra il 24 e il 43 per cento a seconda del metodo utilizzato per identificare il fenomeno. Numerosi studi hanno tentato di approfondire gli effetti dell'HFT sul funzionamento dei mercati di strumenti finanziari, con particolare riguardo a liquidità, efficienza informativa, stabilità e volatilità. Il presente lavoro analizza l'impatto dell'HFT sulla volatilità dei prezzi dei titoli negoziati sul mercato azionario italiano nel periodo 2011 – 2013. Lo studio utilizza due diversi approcci per misurare l'attività degli HFT. Il primo prende a riferimento gli scambi effettuati da 14 operatori identificabili come HFTrs sulla base di informazioni pubblicamente disponibili sulla loro strategia operativa (cosiddetti HFT 'puri'). Il secondo include anche l'operatività in conto proprio delle banche d'investimento, poiché vi sono evidenze, avallate dal citato studio dell'ESMA, che parte di tale operatività è basata su tecnologie *high-frequency*. Le due misure rappresentano quindi il limite inferiore e superiore del peso effettivo degli HFTrs sul totale degli scambi. Il lavoro mostra come un incremento esogeno del livello di attività HFT determini un significativo incremento della volatilità dei rendimenti giornalieri. Infatti, a seconda della specificazione utilizzata, un incremento di 10 punti percentuali del peso degli HFT 'puri' sul totale degli scambi determina un aumento della volatilità *intraday* (calcolata su un intervallo di 10 secondi ed espressa su base annua) compreso tra i 4 e i 6 punti percentuali (su un ordine di grandezza della volatilità che si colloca attorno al 15 per cento circa per i titoli inclusi nell'analisi). Considerando invece la misura più ampia di HFT, che include anche l'operatività delle banche d'investimento, l'effetto risulta compreso tra i 3 e i 5 punti percentuali. Il presente studio costituisce la prima analisi empirica sull'impatto dell'HFT sul mercato azionario italiano e contribuisce a chiarirne gli effetti su integrità e ordinato svolgimento degli scambi. Il lavoro è rilevante anche per le implicazioni di *policy* e si inserisce nel dibattito che, nell'ambito del processo di revisione della direttiva MiFID, ha condotto all'introduzione per la prima volta in Europa di un insieme di regole specifiche tese a mitigare i possibili riflessi negativi sui mercati finanziari del trading algoritmico e ad alta frequenza.

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Si ringrazia Francesco Scalese per il prezioso contributo nella raccolta dei dati e nella costruzione del dataset. Errori e imprecisioni sono imputabili esclusivamente all'autore. Le opinioni espresse nel lavoro sono attribuibili esclusivamente all'autore e non impegnano in alcun modo la responsabilità dell'Istituto. Nel citare il presente lavoro, non è, pertanto, corretto attribuire le argomentazioni ivi espresse alla Consob o ai suoi Vertici.

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Abstract

The huge increase of HFT activity in recent years has posed the crucial question of whether it is beneficial for financial markets to both researchers and regulators. Recent academic research has studied the impact of HFT on different measures of market quality, such as liquidity, transaction costs, market integrity and efficiency, though the results are sometimes non conclusive. This study focuses on the impact of HFT on stock price volatility over the period 2011-2013 for a sample of 35 blue chips traded on Borsa Italiana. High frequency traders (HFTrs) are identified according to two methods. The first one, based on public information on the trading strategies of market participants, led us to identify 14 traders (so called 'pure' HFT firms). The second one includes the main investment banks active in the European markets, since they carry out some proprietary trading which could take the form of HFT (as stemming from the evidence reported in ESMA, 2014). These approaches allow the identification of a lower and upper bound for the actual share of HFT on total trading volume. Potential endogeneity of HFT is controlled through an instrumental variable approach, using as an instrument the introduction of a new trading platform that eased the HFT activity by decreasing the latency. Results show that an exogenous increase of HFT activity causes a statistically and economically significant increase in volatility. In details, an increase by one standard deviation of HFT activity carried out by 'pure' HFT firms raises volatility by an amount between 0.5 and 0.8 standard deviations. This means that, if HFT activity increases by 10 percentage points the annualized intraday volatility increases by an amount between 4 and 6 percentage points depending on the specification used. If we also take into account the activity carried out by investment banks the impact of an increase by 10 percentage points of HFT activity leads to an increase of annualized volatility by an amount between 3 and 5 percentage points. This paper adds to the existing literature by providing new empirical evidence from the Italian market. Furthermore, it contributes to the policy debate, which had recently led the European regulators to introduce new rules aimed at mitigating possible negative effects of HFT.

JEL Classifications: G12, G14, G19, D4.

Keywords: high-frequency trading, algorithmic trading, electronic trading, volatility, market quality.

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The author thanks Francesco Scalese for very helpful contribution on the construction of the database used in this study. Of course, the author is the only responsible for errors and imprecisions. The opinions expressed here are those of the author and do not necessarily reflect those of Consob.

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1 Introduction

In recent years technological progress and financial innovation have spurred the development of trading activities based on algorithms, using real-time market data as inputs and providing trading decisions as outputs, through the submission, modification or cancellation of orders on different trading venues.

The high-frequency trading (hereinafter 'HFT') represents a subset of the algorithmic trading (hereinafter 'AT') characterized by a very high operating speed. High frequency traders are very fast in acting on the financial markets, thanks to the use of a specific technology, software and hardware, and to the availability of services reducing the so called latency, that is the time it takes an order to reach the trading venue. An example of service reducing latency is the colocation that allows traders to locate their computers in close proximity to the trading venue.

HFT is generally considered as a particular market practice based on the fast acquisition, processing and reaction to market information. High frequency traders (hereinafter 'HFTrs') generally show some features that distinguish them from the other market participants, such as the significant investment in technology, the use of complex automatic algorithms, the high number of orders relative to the number of trades.[1]

However, these features do not characterize all HFTrs because of the extreme heterogeneity of this class of market participants using different strategies. For this reason, it is very difficult to define the HFT phenomenon in a precise and exhaustive way.

The AT and, even more, the HFT experienced large and rapid growth in recent years raising concerns about potential risks for market integrity and stability. The crucial question is whether the growing participation of HFTrs to the financial markets is beneficial or harmful to both other market players and markets themselves.

HFT may pose in fact significant risks on order trading and market integrity because the strategies adopted by algorithmic traders could be more interrelated than those used by traditional traders. Moreover, if market conditions are unstable, HFT can further exacerbate sudden movements in prices amplifying market trends and causing disorder in transactions. The impact of HFT activity on price discovery could be negative if the technological advantage of HFTrs discourages well-informed slow traders to operate on transparent trading venues preferring dark pools.

HFT could also have an impact on liquidity. Despite several studies illustrate that HFT has a positive effect on market liquidity, the operating evidence suggests, instead, the destabilizing effect of HFTrs in cases of market turmoil. In fact the liquidity provided by HFTrs not always rely on contractual market-making obligations. For

1 Other distinguishing features are the implementation of proprietary trading, the preference for highly liquid instruments, the of use specific services offered by the trading venues, such as co-location, to improve their operating speed, the high turnover in their portfolio, etc.

this reason it could vanish very shortly and often in conditions of significant stress when the market would mostly need it.

Economic theory has identified some strategies that can cause the trading book's misrepresentation and, as a consequence, can foster potential market manipulation. These strategies are particularly suitable to HFTrs, since they need a high operating speed to be carried out.

Finally, HFT can affect volatility. In particular, the causal link between HFT and volatility seems to act in two ways: on one hand HFT may be more profitable in context of high volatility and, on the other hand, HFTrs massive participation may affect volatility and enhance large price variations.

This paper focuses on this last issue, that is the relationship between HFT activity and single stock volatility. Our results show that in all the model specifications, the impact of HFT activity on volatility is positive and highly significant for both the proxies of HFT activity used. Moreover, the impact of HFT seems to be higher than the impact of other variables able to affect volatility and used as controls.

This paper provides new empirical evidence of the impact of HFT on market quality. To our knowledge, it is the first work on this field focused on the Italian equity market. It has important policy implications since it sheds light on the possible negative effect deriving from a market practice becoming increasingly widespread in the last decade. Regulators across the globe have already taken action in this area. In Europe, the MiFID II regulation introduced a series of safeguards both on market participants who use algorithms and on trading venues where algorithmic and high-frequency trading takes place.

The paper is organized as follows. In Section 2 we provide a brief review of the empirical literature on the relationship between HFT and volatility. Section 3 describes the sample and the approach used in the identification of HFT activity. In section 4 the methodology used in the analysis is presented, while in Section 5 we discuss the results. Section 6 concludes.

2 Literature review

The growing evidence on HFT has not reached unambiguous empirical findings about its effects on market quality. Some scholars argue that HFT activity can be beneficial in terms of increasing liquidity, reducing volatility and improving price discovery. Other scholars highlight undesirable effects, especially during periods of significant market turmoil.

This ambiguity is also due to differences in the approaches used by researchers to overcome some methodological limitations, which may severely hinder the analysis. First, the identification of high frequency traders (HFTrs) may be either direct or indirect: on one hand, researchers directly identify a list of operators assumed to be HFT while, on the other hand, researchers identify the HFTrs according to their operating features. Both these methods have some drawback and they can give only a partial view of the phenomenon, as we will discuss in Section 2. Therefore, depending on the identification method used and on the particular measure chosen, the HTF activity may be either underestimated or overestimated. Second, identifying a causal link between HFT and market quality is problematic because of endogeneity: market quality may be both a cause and a consequence of an increase in HFT activity. Therefore, qualitative results exhibit a certain variation, depending on the approaches employed to identify HFTrs and to solve the endogeneity issue.

Among the scholars finding positive effects of HFT activity on market quality, Hendershott and Riordan (2009), using data on 30 DAX stocks from Deutsche Boerse, show that algorithmic trades can smooth out liquidity over time, because they consume liquidity when it is cheap and supply liquidity when it is expensive, and can contribute positively to the price discovery process. On the other hand, they do not find evidence of algorithmic trading exacerbating volatility during periods of market turbulence.

Hagströmer and Nordén (2013), using data from NASDAQ-OMX Stockholm, distinguish different HFT strategies and compare the behaviour of market making HFTrs relative to the HFTrs carrying out an opportunistic behaviour (through arbitrage and momentum strategies). They show that both market making and opportunistic strategies mitigate intraday price volatility.

Broogard et al. (2014) do not find direct evidence that the HFT increases market instability. They use trading data of 26 firms identified by NASDAQ as engaging primarily in HFT activity. They distinguish price movements in two components: a permanent component that is interpreted as information and the transitory component that is considered as a pricing error (also called noise or short-term volatility). Their findings highlight that HFTrs overall trade in the direction of reducing transitory pricing errors (or short-term volatility) both on normal days and during days of high volatility and market turbulence.

Chaboud et al. (2014) investigate whether the HFTrs' propensity to follow strategies that are more correlated than those of non-algorithmic traders has a destabilising effect on price discovery and volatility in the foreign exchange market. In other words, they test whether the lower diversity in the market due to HFTrs' herding behaviour causes larger prices movements.[2] Despite the high correlation among algorithmic trading strategies, Chaboud et al. (2014) do not find a causal relationship between algorithmic trading and exchange rate volatility. On the contrary, algorithmic trading is associated with a lower volatility.

Among the studies raising concerns about HFT, Boehmer's et al. (2014) find that the rise of algorithmic trading between 2001 and 2011 is associated, on average, with more liquidity, faster price discovery but also higher volatility. These results are

2 Highly correlated strategies do not necessarily lead to a higher volatility. For example, if many algorithmic traders use highly correlated arbitrage strategies, volatility may be little affected or may even decrease through a better functioning of the price discovery. On the contrary, if the correlation of strategies results in many traders taking the same side of the book, then the unbalances in the order flows could bring to sudden price movements and higher volatility.

drawn for the activity carried out by algorithmic traders (defined as traders with access to fast trading technology, showing a high order traffic) on a sample of securities listed in 42 markets. The evidence is robust to stock specific characteristics and consistent across different markets but not across different types of stocks.[3]

Zhang (2010), using quarterly data for the 1985–2009 period, shows a positive correlation between HFT and stock price volatility, after controlling for volatility driven by changes in firm fundamentals or other exogenous factors. In more details, HFT is found to lead to stock prices overreaction to news as it hinders the incorporation of information about fundamentals into asset prices. The detrimental effects on volatility are higher for large cap stocks and during market turbulences. Moreover, consistently with the hypothesis that HFTrs mainly take advantage of large trades typically carried out by institutional investors, stocks with high institutional ownership seem to suffer more the negative impact of HFT.

A few studies find several off-setting effects of HFT on volatility and therefore do not reach a clear conclusion. Benos and Sagade (2012) focus on a sample of four stocks included in the FTSE 100 Index during a period of one week randomly selected. They find that HFT raises both 'good' volatility and 'excessive' volatility (being the former the only one reflecting the arrival of new information about fundamentals) and, therefore, do not provide a clear evidence about the HFT welfare implications.[4]

Also Bershova and Rakhlin (2013), focusing on UK and Japan equity markets during the first half of 2010, show that the increase in short-term intraday volatility and in trading costs due to HFT is more than offset by the narrowing of bid-ask spreads.

Evidence on the impact of HFT on volatility is provided also by empirical researches directly focusing on the effect on liquidity. Liquidity and volatility are generally negatively correlated: as the former rises the latter lowers. However, depending on the liquidity measures used, a positive correlation may arise. Dichev et al. (2011) analysed the effect of trading volumes on stock volatility in various US stock exchanges (NYSE, AMEX, and Nasdaq) during a period of 47 years (from 1962 to 2009). They find that higher trading volumes can be destabilizing and produce their "own volatility above and beyond that based on fundamentals".[5]

3 In contrast to the average effect, in small stocks a high algorithmic trading activity reduces liquidity. Moreover, in small priced stocks and high-volatility stocks the impact of algorithmic trading on liquidity is negligible, although it leads to a greater increase in volatility.

4 However their small cross-section sample does not allow them to draw conclusions about the overall impact of HFT on market quality.

5 An example is represented by the flash crash of May 6, 2010 occurred in the e-Mini S&P 500 futures contracts, that is characterized by very high liquidity conditions. During the crash, the liquidity on the market abruptly disappeared causing sudden and very large price movements. Hence, although it can be generally argued that a deep market absorbs shocks better than a market with low liquidity, this may not always hold true. Under certain circumstances, a highly liquid market can be more exposed to herding behaviour and, hence, to contagion.

The effect of HFT on market liquidity is quite controversial. Several studies illustrate a positive impact,[6] while the operating evidence shows the opposite. Albeit HFTrs provide liquidity to other traders, they act as informal market makers and as such are not subject to affirmative obligations, such as requirements for continuous liquidity provision on both sides of the market (in contrast to exchange-regulated market makers). Therefore, the liquidity provided by HFTrs is not stable over time, in particular when market instability rises (see Kirilenko et al. 2015).[7] Indeed, the liquidity provided by HFTrs is apparent (so called 'ghost liquidity') and tend to vanish very quickly during periods of high market stress. The ghost liquidity phenomenon can be the result of the HFTrs cross-market activity (Van Kervel, 2014)[8] or of other strategies, such as the so called 'quote-stuffing' (involving entering and almost immediate cancelling a high number of orders on the same stock; Egginton et al., 2014).[9]

The impact of HFT on market quality (in terms of liquidity, volatility, price efficiency, fair access to the market etc.) has also been investigated by many regulatory authorities. In the US, the Securities and Exchange Commission (SEC) published a call for comments in 2010 trying to address various aspects of the risks posed by HFTrs' massive participation to financial markets. In June 2014, SEC Chairman announced that the agency was pursuing several reform proposals related to HFT activity in response to concerns deriving from the potential negative impact of this practice on markets. Moreover, from 2010 to 2014, the SEC has adopted a number of regulatory initiatives able to affect the HFT activity (i.e. the Large Trader Reporting Rule adopted in 2011 or the new circuit breakers system adopted in 2012). In the UK, the Treasury Foresight Committee analysed the phenomenon in 2011 reaching the conclusion that, even if there is no direct evidence of HFT activity causing an increase in volatility, under certain circumstances it can amplify market instability.

Also the European authorities are involved in the study of this phenomenon. In 2010, CESR (now ESMA) published a Call for Evidence on 'Microstructural issues of the European equity markets' as part of preliminary works about MiFID review process[10] highlighting the relevance of the analysis of HFT phenomenon. In 2014 ESMA, published an economic report dedicated to the HFT in the European equity markets describing its features. ESMA shows that HFT activity accounts for a different amount of total trading according to the different identification methods used. In particular using the direct identification approach the HFT accounts for 24% of value traded in Europe, while using the indirect identification method (based on the lifetime of orders) it accounts for a higher amount (43% of the value traded in Europe). Moreover

6 Among the others, see for example Menkveld (2013), Hasbrouck and Saar (2013), Riordan and Storkenmaier (2011).

7 Anand and Venkataraman (2014) show that informal market makers are less likely to provide liquidity during market turbolences.

8 In order to increase the execution chances, HFTrs enter their orders on several platforms. When execution takes places in one of these platforms, the "twin" order entered in the other venues is often cancelled.

9 Egginton et al. (2014) estimate that more than 74% of securities listed on the NYSE experienced at least one episode of intense quoting activity during 2010. They find also that, during these episodes of 'quote stuffing', stocks experienced a decline in liquidity and an increase in trading costs and short term volatility.

10 See CESR (2010). The new European regulation (MiFID II and MiFIR) contains many rules regarding algorithmic trading and HFT.

this report also looked at the HFT activity carried out by investment banks. In details, under the indirect identification approach ESMA (2014) finds that the 43% HFT share of value traded in Europe is split in 19% provided by operator classified as pure HFT firms, 22% by investment banks and 2% by other market participants. Hence the HFT activity carried out by investment banks is significant.

ESMA also analysed the use of colocation that represents a rough proxy for HFT. Using aggregate data ESMA shows that colocation services are used not only by pure HFT but also by investment banks. In particular, 80% of pure HFT firms use a colocation services in at least one trading venue, while the investment banks using colocation are the 37% of the total.

As for the regulation, in 2014, the "MiFiD II/MiFIR package" was adopted with the first common HFT-related regulation in Europe and a regulatory framework aiming at increasing transparency in the European financial markets . Indeed, MiFID II explicitly defines the HFT activity and introduces specific rules for those market operators engaged in such activity. MiFID II/MiFIR Level 2 regulation in this area will provide additional details and clarification as to the definitions of algorithmic trading and high frequency algorithmic trading technique.

3 The sample

The dataset contains trades on 35 major stocks listed on Borsa Italiana and included in FTSE MIB Index throughout the period 2011 – 2013. In order to compute intraday returns we use all trades occurred during continuous trading sessions. The empirical analysis is implemented using data on a daily frequency.

We do not use data on orders because an analysis based on orders covering a 3-years period would be too computationally intensive.

3.1 Identification of HFT activity

One of the key problem of the empirical research on this subject is the identification. Indeed, HFT activity could be carried out by different kind of operators characterized by different trading strategies. As a consequence, all the measures of HFT activity proposed in the literature are just proxies of the real HFT and may lead to different results.

Empirical studies employ either a direct or an indirect approach. The first method directly identifies as HFTrs those market participants whose primary business is the HFT carried out on proprietary basis. Usually, this information is provided by the trading venues. The second method identifies HFTrs according to their operational features. In this case, data on orders are needed in defining the behaviour of the different market participants and in recognizing those that can be considered HFTrs.

Among the studies based on a direct identification method we find Brogaard, Hendershott and Riordan (2009) and Zhang (2012) that all use a list of 26 firms obtained by NASDAQ. Although easy to apply, this method has some shortcomings. First of all it does not include the trading activity by HFT desks of investment banks, which may underestimate the phenomenon. As highlighted before, ESMA has shown that the HFT activity carried out by investment banks could be significant.

Another drawback of such identification method is that it entails the use of aggregate data on HFT activity, regardless of the different strategies used, so that the estimate of the impact of HFT behaviour on market quality will depend on the predominant strategy in the sample (Biais and Foucault, 2014).

The studies based on the indirect identification of HFT activity use different measures in order to quantify the phenomenon. For instance, many studies calculate the ratio between orders sent to the venues and trades actually carried out (order-to-trade ratio, hereinafter 'OTR'), which is higher for HFTrs than for slow traders (Boehmer's et al., 2014, and Hendershott et al., 2010). Others focus on account-level data and identify as HFTrs market participants trading with own funds, having open positions close to zero at the end of the day and carrying out a significant number of small transactions (Kirilenko et al., 2011, and Hagströmer and Nordén, 2013).

These methods of indirect identification have some drawback. Given the high heterogeneity of HFT strategies, focusing on few features could bring to select only a subset of strategies, resulting in a partial view of the phenomenon. For instance, Hagströmer and Nordén (2013) show that opportunistic HFTrs (those that consume liquidity) have typically a lower OTR than the HFTrs acting as market-makers (those that supply liquidity). Hence, the use of OTR cannot be considered as a 'neutral' method because it bias the HFT sample towards those operators having a good impact on the markets.

The lack of an exact measure of the HFT activity is one of the causes for the high heterogeneity in the results reached by the empirical economic literature.

This study identifies HFT activity through the direct approach, focusing on a list of HFTrs carrying out, as primary activity, the trading at high frequency.

Using a direct approach, we focus on those market participants that can be defined as 'pure' HFT firms. The list of 'pure' HFT firms is based on public information on the trading strategies of market participants. We draw up this list starting from the list of 20 HFT operators acting on the European trading venues identified by ESMA.[11] Our list is constituted by 14 firms (out of 20) operating in the Italian equity market. The market share of trading carried out by these agents (in terms of turnover) represents a lower bound for HFT activity (named HFT small).

In fact, such measure of HFT activity does not include HFT activity related to other firms and in particular to investment banks with HFT desks. Hence, in order to give a better representation of HFT activity, we consider HFT trading carried out by investment banks too. Unfortunately, data on trades do not allow us to distinguish

11 ESMA draw up this list together with the National Authorities competent for 11 trading venues. They classified market participants as HFTrs, investment banks and other traders. HFTrs were identified with reference to their primary business. ESMA classified 20 entities (out of 394) as HFTrs. See ESMA (2014).

proprietary trading carried out by investment banks through HFT desks from those proprietary trading realized through non-HFT desks. Therefore, trading activity of investment banks can only be computed as a whole, resulting in a proxy for HFT activity that may overestimate the phenomenon. Such proxy is computed with reference to a list of 14 HFT firms and 11 investment banks.[12] This proxy, named 'HFT large', may obviously overestimate HFT activity so that it represents an upper bound for HFT share of trading.

4 The model

We study the impact of HFT activity on stock specific volatility of the main Italian listed companies. To this end, we estimate a model to capture the impact of an exogenous increase of HFT activity on stock specific volatility. More specifically, we first calculate a measure of intraday volatility with reference to each stock included in the analysis. Then we define a set of control variables able to exogenously affect volatility.

Finally, we address the endogeneity issue that arises from the fact that the causal link between the HFT activity and volatility acts in two ways: on one hand, HFT appears to be more profitable in case of high volatility; on the other hand, HFTrs massive participation to the markets affects volatility because it may lead to large price variations.

We solve the endogeneity issue by focusing on a specific technological change: the migration of Borsa Italiana's cash markets to a ultra-fast new platform Millennium Exchange, occurred in 2012. This migration fostered the HFT participation to the trading activity. We construct a dummy variable taking the value of one for the days after the migration to Millennium and zero otherwise and we use it as an instrument for HFT activity. As we will highlight later, this variable satisfies the exclusion restriction. Using an instrumental variable approach we can estimate the impact of an exogenous increase of HFT activity on stock specific volatility.

4.1 The dependent variable

Our dependent variable is the ten-seconds intraday realized volatility. For each trading day, we compute the standard deviation of the returns over an interval of ten-seconds according to the following formula:

$$RV_t^{10s} = \sqrt{\frac{\sum_{j=1}^{d}(r_i - \bar{r})^2}{d-1}}$$

12 The investment banks included in the list are global firms active in underwriting listed equities and equity-linked products carrying out market making activities in the European markets.

where r_i are the ten-seconds stock returns calculated as the natural logarithm of the ratio between the mean price in interval *j* and the mean price in the interval *j-1* and *d* is the number of ten-seconds intervals *j* within one day.

The presence of market microstructure (such as bid/ask bouncing, that is the bouncing of trade prices between the bid and ask sides of the market) can induce a bias in our measure of realized volatility. In order to control for the robustness of our results to the measure of volatility used, we run the model on the realized volatility computed on higher time intervals of one minute, five minutes and ten minutes.

4.2 Control variables

A first set of controls includes indicators of the macroeconomic context that can affect volatility. In details, we included the FTSE MIB ten-seconds realized volatility on day *t*, the 3-months Euribor interest rate and the ten-years Btp-Bund spread.

FTSE MIB ten-seconds realized volatility is expected to be positively correlated to stock specific volatility. As for the 3-months Euribor interest rate, a lower interest rate positively affect liquidity in financial markets. Moreover, at the macro level, lower short-term rates may reflect an easier monetary policy that may induce expectations of a more robust economy. The 3-months Euribor should be positively related to stock specific volatility given that a decrease in interest rates results in a decrease in volatility of stock returns. The ten-years Btp-Bund spread should impact positively on the volatility of Italian stocks returns, being this variable an indicator of the market sentiment on the state of the Italian economy fundamentals. A rise of the ten-years Btp-Bund spread mirrors a rise in the uncertainty on the Italian financial market bringing to a surge in volatility.

We include in our analysis a second set of control variables representing stocks specific characteristics.[13] This set of variables is constituted by the daily market capitalization of stock *i*, the daily bid/ask spread, the inverse of daily price and the fragmentation index of each stock *i*.

Market capitalization is a measure of stock liquidity usually negatively correlated with volatility so that the higher the stock market capitalization the lower the volatility.

The bid/ask spread represents a measure of transaction costs and a rough measure of liquidity. The economic literature suggests that it is positively related to volatility.[14]

13 Other variables (macro and stock specific) were considered in the analysis but they were excluded because of their high correlation with the explanatory variables included. See the appendix for the correlation matrix of all the variables considered.

14 This positive relationship is formalized in a model developed by Bollerslev and Melvin (1994). However we cannot consider bid/ask spread as strictly exogenous because it can be affected by volatility. For this reason in our analysis we use also the one-period lagged value of bid/ask spread. In this specification sign and significance of all coefficients do not change but the partial F-statistic on Millennium does not reject the hypothesis of weak instruments.

The inverse of price represents a proxy for transaction costs. Indeed, it is associated to the minimum tick size, that is the smallest increase (tick) by which the price of a stock can move. In European markets, tick sizes vary according to the price of the stock, with larger increases at higher prices. Economic literature argues that incentives for liquidity provision have declined with the reduction of the tick sizes established by the trading venues. For example, Harris (1996) notes that smaller tick size lowers the cost of stepping ahead of standing limit orders and thereby discourages liquidity provision. On the other side, higher tick sizes imply higher transaction costs because it is more expensive to achieve a price priority with a high minimum price movement.[15] For this reason it is not possible to say, a priori, which of the two effects would prevail. Hence the sign of this variable is ambiguous.

The relationship between fragmentation and volatility is not straightforward as well. Some researchers find that an increase in fragmentation could raise volatility.[16] On the contrary, more recent studies show that stocks characterized by a high fragmentation exhibit a lower volatility.[17]

4.3 Finding an instrument for HFT activity

As said, when studying the impact of HFT activity on volatility, the endogeneity issue is a major concern. Volatility may be both a cause and a consequence of an increase in HFT activity. Indeed, as highlighted before, the link between the HFT activity and stock prices volatility may act in two ways: on one hand, HFT appears to be more profitable in case of high volatility; on the other hand, HFTrs massive participation to the markets may affect volatility and enhance large price variations because it is carried out according to short-run strategies.

To solve the endogeneity issue, many empirical studies employ a difference-in-difference methodology that analyses the impact of an exogenous shock to the 'level' of HFT activity (i.e. a change in market microstructure or the introduction of a specific policy measure) involving only a subset of stocks. This approach allows the comparison between variations in market quality measures across the stocks affected by the shock and those not affected before and after the shock occurred.

Other studies focus on a specific change in technology or market microstructure (involving all the stocks traded in that market) that can foster or hinder the HFTrs participation to the trading activity. By using the technological change as an instrument for HFT activity, it is possible to estimate the impact of HFT activity on market quality through an instrumental variables approach. A variable describing a technological change affecting HFT activity generally satisfies the exclusion restriction: it is causally related to HFT activity by construction and it is not related to the market quality measure which may be affected by HFT. Hence the instrument allows to identify the causal link between HFT activity and a change in market quality.

15 See Gai, Yao and Ye (2013) who argued that HFTs are more active in lower priced stocks.

16 See Mendelson (1987) and Madhavan (1995).

17 See Fioravanti and Gentile (2011) for an analysis of the European markets.

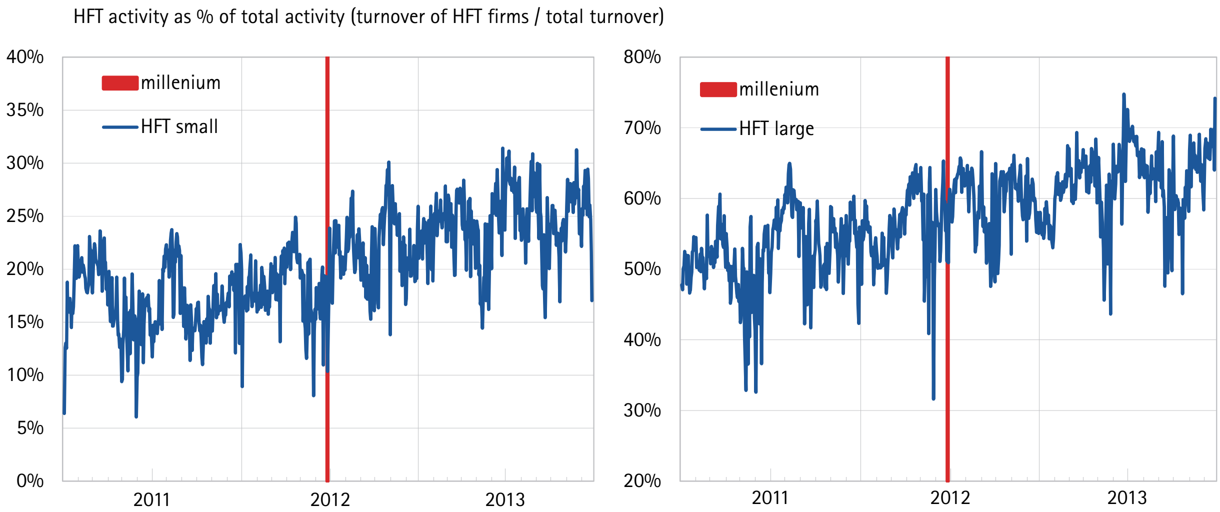
This study follows the instrumental variables approach by focusing on a specific technological change occurred on the Italian market in 2012.

We identify the exogenous shock in the migration of Borsa Italiana's cash markets to a new ultra low-latency trading platform, named Millennium Exchange. This trading platform offers to the market participants the possibility of operating with a lower latency. In fact, the migration to Millennium implied a new configuration of Borsa Italiana's servers in order to bring the hardware closer to its markets and ensure greater efficiency and higher speed.

Hence it is reasonable to assume that the migration to Millennium led to an increase of the HFT activity.

Figure 1 shows the HFT trading activity as a percentage of total trading in the period under analysis (i. e. turnover of HFTrs relative to total turnover). The migration to Millennium was completed on June 25th, 2012. After that day HFT activity, both small and large, rose to higher levels on a permanent basis. Obviously this dynamics appears to be more pronounced for HFT small (that is for the proxy that refers only to the activity of 'pure' HFT firms).

Figure 1 – HFT activity as percentage of total activity on the major Italian stocks
(data on a daily frequency, 03/01/2011 – 20/12/2013)



The test for the statistical significance of the difference in mean values of HFT activity in the time interval before and after the migration to Millennium rejects the hypothesis of equality of means for both HFT small and HFT large; moreover, both the p-value and the confidence interval of 99% show that the mean after the migration is higher than the mean of the preceding period. Hence, the test confirms the increase of the HFT activity after the implementation of the new trading platform.[18]

18 The Augmented Dickey-Fuller (ADF) test for unit root rejects the hypothesis of unit root with a test statistic equal to -3.597 (p-value equal to 0.0058) for HFT small and -3.856 (p-value equal to 0.0024) for HFT large. The ADF test in-

Table 1 – HFT activity before and after the migration to Millennium
(statistics calculated on daily data)

	HFT small			HFT large		
	before	after	t-test	before	after	t-test
mean	17.4%	23.5%	-25.0512***	53.4%	61.4%	-20.9822***
median	17.2%	23.9%		53.3%	62.2%	
std. dev.	0.032	0.035		0.055	0.050	
maximum	24.9%	31.4%		65.3%	74.7%	
minimum	6.1%	10.4%		31.6%	43.6%	

The same test applied on the FTSE MIB index realized volatility does not reject the null hypothesis of equality in mean values of volatility before and after the migration to Millennium. Both the tests confirm that the migration to Millennium represents a credible instrument because it is directly related to the independent variable of interest (HFT activity) but unrelated to the dependent variable (volatility).

4.4 The model specification

In order to analyse the impact of HFT on volatility we implement a panel two-stage instrumental variables fixed effect estimation.[19]

In the first stage a dummy variable *Mill*, taking the value of one for the observations after the migration to Millennium and zero otherwise, is used to instrument the HFT activity, with other macroeconomic ($C_{i,t}$) and stock specific characteristics ($X_{i,t}$) controlled for. Stock fixed effects (F_i) are included in all the model specifications to capture time-invariant stock characteristics that may be related to HFT activity.

The general model design in the second-stage has the following equation:

$$vol_{\,i,t} = \beta_i HFTinstr_{i,t} + \theta_i C_{i,t} + \vartheta F_i + \varepsilon_{\,i,t} \tag{2}$$

where $vol_{i,t}$ is the ten-seconds realized volatility for stock *i* in day *t*, $HFTinstr_{i,t}$ is the fitted value of the first-stage regression, where HFT activity is regressed on the dummy variable *Mill* and the other explanatory variables. $C_{i,t}$ represents a set of control variables and includes indicators of the macroeconomic context that may exogenously affect volatility (the FTSE MIB ten-seconds realized volatility on day *t*, the 3-

cludes up to five lags for HFT small and up to four lags for HFT large, selected using the sequential testing procedure.

19 In order confirm our theoretical preference for a fixed-effects model (we believe that stock differences matter and are persistent along time) we run a Wald test for the jointly significance of the coefficients on individual dummy variables (i.e. fixed-effect). The test rejects the hypothesis of absence of fixed effect (Chi-statistics equal to 1003.18) and confirms that time-invariant stock specific characteristics matter in this context.

months Euribor interest rate and the ten-years Btp-Bund spread). F_i represents the stock fixed effects included to capture time-invariant stock specific characteristics that may be related to volatility.

Starting from this general specification we also implement the estimation by adding as explanatory variables other stock specific variables in order to control the robustness of results to the introduction of other factors able to affect volatility. In this way we should rule out the possibility that the coefficient of HFT activity captures other effects that are not directly linked to HFT participation to the market.

With the inclusion of stock specific explanatory variables the second-stage equation takes the form:

$$vol_{\,i,t} = \beta_i HFTinstr_{i,t} + \theta_i C_{i,t} + \gamma_i X_{i,t} + \vartheta F_i + \varepsilon_{\,i,t} \qquad (3)$$

where X_i represent a set of stock specific control variables that includes the market capitalization of stock *i* in day *t*, the daily bid/ask spread, the inverse of price of stock *i* in day *t*, the fragmentation index of each stock *i* in each day *t*. Details on the expected sign of these variables are reported in the previous section.

In order to take into account for the high autocorrelation of the dependent variable, both a static and a dynamic specification was estimated. Residuals are robust to both heteroschedasticity and cross-sectional dependence.

5 The results

We implement estimations using the two proxies of HFT activity described before, namely *HFT small* and *HFT large*.[20]

We use standardized data in order to improve numerical efficiency and to be able of properly comparing the magnitude of the coefficients. However, results of estimations using the original series do not change in sign and significance. For robustness reasons we run five alternative models which mainly differ from each other for the list of explanatory variables used.

Table 2 shows results of the first-stage equation of the dynamic model and confirms that the relationship between HFT activity and the dummy variable *Mill* is strongly positive and significant. This relationship is robust to the inclusion of several control variables (macroeconomic or stock specific).

20 The Breitung test for unit root in panel data confirms the stationarity of both HFT small and HFT large at all significance levels, with a test statistic equal to -5.3550 and to -13.1360, respectively.

Table 2 – Results of the first-stage regression in the dynamic specification

dependent variable: HFT activity	Model 1L		Model 2L		Model 3L		Model 4L		Model 5L	
proxy for HFT activity	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*
Millennium	0.348***	0.426***	0.331***	0.397***	0.366***	0.444***	0.379***	0.470***	0.330***	0.323**
	[0.002]	[0.000]	[0.002]	[0.000]	[0.002]	[0.001]	[0.002]	[0.001]	[0.005]	[0.008]
market cap			0.060*	0.107*	0.061*	0.107*	0.036	0.056	0.010	-0.022
			[0.061]	[0.058]	[0.060]	[0.058]	[0.252]	[0.142]	[0.753]	[0.547]
bid/ask spread					0.027	0.037	0.032*	0.046	0.020	0.012
					[0.105]	[0.210]	[0.061]	[0.134]	[0.202]	[0.654]
inverse of price							-0.556***	-1.159***	-0.300	-0.378**
							[0.005]	[0.000]	[0.149]	[0.038]
fragmentation index									0.193***	0.586***
									[0.000]	[0.000]
FTSE MIB volatility	0.006	0.038***	0.007	0.040***	0.007	0.040***	0.007	0.040***	0.002	0.025***
	[0.287]	[0.000]	[0.224]	[0.000]	[0.213]	[0.000]	[0.231]	[0.000]	[0.704]	[0.000]
3-months Euribor	-0.377***	-0.298***	-0.382***	-0.306***	-0.318***	-0.305***	-0.385***	-0.313***	-0.399***	-0.355***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Btp-Bund spread	0.075	0.097	0.100*	0.142*	0.90	0.128*	0.105**	0.160***	0.092**	0.121***
	[0.155]	[0.124]	[0.077]	[0.058]	[0.107]	[0.073]	[0.037]	[0.007]	[0.048]	[0.011]
Lag (1) volatility	-0.009	0.037	0.005	0.063*	0.004	0.060*	0.004	0.062*	-0.002	0.043
	[0.726]	[0.354]	[0.813]	[0.068]	[0.870]	[0.073]	[0.836]	[0.055]	[0.924]	[0.124]
Partial F-statistic (Ist stage)	11.85	18.60	11.04	16.03	11.33	13.04	11.79	12.82	9.03	8.07
N. of observations (total)	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460

*, **, *** indicate a significance level of 90%, 95% and 99%, respectively.

Results of the first-stage regression confirm that the dummy variable *Mill* can be considered a good instrument for HFT activity.[21] This holds for both the proxies of HFT activity used (*HFT small* and *HFT large*). Only in the model 5 (that includes the fragmentation index among the explanatory variables) the dummy on Millennium fails the partial F-test (the F-statistic takes a value of 9.03 and 8.07 respectively for HFT small and HFT large). This result could be due to the very high significance of the fragmentation index as factor affecting the level of HFT activity. This is not unexpected because many HFTrs have an intense cross-market activity so that a positive correlation between the two variables arises.[22]

21 Four model specification (out of five) show a partial F-test with a value greater than 10 (rejecting the hypothesis of weakness of Millennium as instrument for HFT activity).

22 As shown in ESMA Economic Report (2014), HFTrs are more likely to arbitrage across trading venues that other market participants.

Table 3 presents the results of the second-stage equation for both *HFT small* and *HFT large*.[23] All the model specifications have a high overall significance (second-stage F-statistic reported).

Table 3 – The impact of HFT activity on stock volatility in the static model

dependent variable: realized volatility	Model 1		Model 2		Model 3		Model 4		Model 5	
proxy for HFT activity	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*
HFT activity	0.957***	0.768***	1.115***	0.902***	1.357***	1.078***	1.313***	1.021***	1.495***	1.473***
	[0.003]	[0.000]	[0.003]	[0.000]	[0.002]	[0.001]	[0.002]	[0.001]	[0.006]	[0.007]
market cap			-0.284***	-0.302***	-0.298***	-0.317***	-0.262***	-0.258***	-0.236***	-0.173**
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.014]
bid/ask spread					0.067**	0.060*	0.063**	0.054*	0.073**	0.082*
					[0.013]	[0.052]	[0.018]	[0.069]	[0.013]	[0.052]
inverse of price							0.741**	1.195**	0.492*	0.603*
							[0.017]	[0.003]	[0.092]	[0.054]
fragmentation index									-0.263**	-0.839**
									[0.016]	[0.012]
FTSE MIB volatility	0.065***	0.039**	0.058***	0.026*	0.057***	0.019	0.058***	0.022	0.063***	0.024
	[0.000]	[0.003]	[0.000]	[0.070]	[0.000]	[0.272]	[0.000]	[0.187]	[0.000]	[0.176]
3-months Euribor	0.753***	0.609***	0.809***	0.644***	0.900***	0.693***	0.888***	0.684***	0.980***	0.887***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]
Btp-Bund spread	0.472***	0.450***	0.305***	0.269***	0.253**	0.216**	0.237**	0.191**	0.238**	0.175
	[0.000]	[0.000]	[0.001]	[0.002]	[0.016]	[0.030]	[0.022]	[0.040]	[0.034]	[0.128]
F-statistic (IInd stage)	83.86	79.63	62.24	71.48	46.97	50.62	42.44	51.66	33.70	27.29
Partial F-statistic (Ist stage)	12.35	19.70	11.68	17.65	11.72	14.43	12.22	14.21	9.30	8.93
N. of observations (total)	26,495	26,495	26,495	26,495	26,495	26,495	26,495	26,495	26,495	26,495

*, **, *** indicate a significance level of 90%, 95% and 99%, respectively.

HFT activity turns out to affect positively volatility across all the models estimated. Therefore, as HFT activity rises the intraday realized volatility of stock returns increases. This is consistent with the hypothesis that the HFTrs' participation to the markets increases the intraday volatility.

Moreover, the impact of an exogenous increase of HFT activity on volatility is highly significant for both the proxies of HFT activity used (small and large). If HFT activity increases by one standard deviation then the stock price intraday realized volatility increases by an amount between one and 1.5 standard deviations if we use as proxy HFT small. This means that, if HFT activity increases by 10 percentage points the annualized intraday volatility increases by an amount between 7 and 12 points

23 We run a Wooldridge's (1995) robust score test for the endogeneity of the HFT activity, that rejects the hypothesis that the variable is exogenous at all level of significance (F-statistics equal to 29.74).

depending on the specification used. If we take into account also the activity carried out by investment banks, the impact on volatility is similar.

However this model does not take into account the autocorrelation of the dependent variable that typically characterizes volatility. A test for serial correlation in the residual of the static model does not reject the hypothesis of no serial correlation in residuals of all the specification used.[24]

In order to solve this problem, we estimate a dynamic model in which the one-period lagged value of the volatility is introduced among the explanatory variables. This model does not fails the test for serial correlation in residuals for all the specifications tested.

In the dynamic model the coefficients on HFT activity remain highly significant but their magnitude decreases in all the specifications and for both the proxies of HFT activity used. Table 4 presents results for this latter specification.

In particular, an increase by 1 standard deviation of the HFT activity causes the stock price intraday realized volatility to increase by an amount between 0.5 and 0.8 standard deviations for HFT small and between 0.3 and 0.8 for HFT large. This means that an increase by 10 percentage points of HFT causes a rise of annualized volatility by an amount between 4 and 6 points for HFT small and between 3 and 5 points for HFT large.

All the other explanatory variables used as control have the expected sign (see section 2 for a discussion) and are significant in nearly all the specifications used.

In particular, as for the macroeconomic context, the controls are positively related to the stock specific intraday realized volatility. An increase in FTSE MIB Index volatility, in short term interest rate and in Btp/Bund spread are signals of a decline of the general economic conditions and of a surge of uncertainty.

As for the variables representing time-varying stock specific characteristics, both market capitalization and the bid/ask spread have the expected sign. Moreover we find that the inverse of price is positively related to the intraday volatility. So a reduction of price results in an increase of volatility. This evidence supports the hypothesis, highlighted in Section 2, that a reduction of tick size discourages liquidity provision bringing to a rise in volatility. Finally, the coefficient of the fragmentation index has a negative sign, confirming that the more fragmented are the exchange of a stock, the lower the intraday volatility should be.

As robustness check we run the same specifications also on the realized volatility computed on higher time intervals of 1-minute, 5-minutes and 10-minutes. Results are reported in the Appendix and do not change in sign in all the model tested. Also the significance of the estimated coefficients remains very high.

24 As shown in Godfrey (1994) in an instrumental variable setting, the test for serial correlation in residuals can be carried out by adding lagged residuals from the model to the other explanatory variables of the model itself and then checking their joint significance.

Table 4 – The impact of HFT activity on stock volatility in the dynamic model

dependent variable: realized volatility	Model 1L		Model 2L		Model 3L		Model 4L		Model 5L	
proxy for HFT activity	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*
HFT activity	0.461***	0.377***	0.566***	0.473***	0.728***	0.601**	0.704***	0.568***	0.794***	0.812**
	[0.003]	[0.000]	[0.003]	[0.000]	[0.002]	[0.016]	[0.002]	[0.001]	[0.007]	[0.011]
market cap			-0.131***	-0.147***	-0.141***	-0.161***	-0.122***	-0.128***	-0.107***	-0.081**
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.032]
bid/ask spread					0.042***	0.040**	0.040***	0.036**	0.045***	0.051**
					[0.004]	[0.024]	[0.005]	[0.030]	[0.004]	[0.032]
inverse of price							0.388**	0.654***	0.257	0.326*
							[0.027]	[0.003]	[0.118]	[0.064]
fragmentation index									-0.136**	-0.459**
									[0.019]	[0.018]
FTSE MIB volatility	0.041***	0.029***	0.038***	0.023***	0.037***	0.019*	0.038***	0.020**	0.040***	0.022**
	[0.000]	[0.000]	[0.000]	[0.005]	[0.000]	[0.077]	[0.000]	[0.044]	[0.000]	[0.036]
3-months Euribor	0.353***	0.291***	0.403***	0.331***	0.469***	0.372***	0.459***	0.366***	0.504***	0.476***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.002]
Btp-Bund spread	0.204***	0.201***	0.142***	0.131***	0.110*	0.098*	0.102*	0.085*	0.101*	0.076
	[0.000]	[0.000]	[0.002]	[0.004]	[0.055]	[0.078]	[0.067]	[0.091]	[0.092]	[0.223]
Lag (1) volatility	0.569***	0.551***	0.538***	0.512***	0.535***	0.501***	0.534***	0.502***	0.538***	0.502***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
F-statistic (IInd stage)	250.67	251.62	189.50	200.11	133.52	137.16	121.47	158.31	100.16	128.68
Partial F-statistic (Ist stage)	11.85	18.60	11.04	16.03	11.33	13.04	11.79	12.82	9.03	8.07
N. of observations (total)	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460

*, **, *** indicate a significance level of 90%, 95% and 99%, respectively.

6 Conclusions

In recent years the rapid spread of HFT activity within the financial markets has fostered research by both academics and supervisory authorities. The crucial question is whether the growing participation of high-frequency traders (HFTrs) to the financial markets is beneficial or harmful to both the other market players and the markets themselves.

Currently, the evidence on HFT has not reached unambiguous empirical findings about its effects on market quality. Unfortunately, the economic literature about this phenomenon suffers some methodological limitation that could affect the qualitative results.

This study focus on the impact of a surge in HFTrs participation to the markets could have on the stock specific volatility. We first identify the HFT activity according to the direct approach, that is we use a list of market operators having the

HFT trading as their primary activity. Such list is constituted by 14 firms (out of 20 HFT firms acting on the European trading venues and identified by ESMA) operating in the Italian equity market. Trading carried out by these traders (in terms of turnover) on 35 Italian stocks represents our proxy for HFT activity. We define also an other proxy for HFT activity by adding the trading activity carried out by 'pure' HFTrs the trading activity carried out by investment banks having HFT desks. This proxy overestimates the HFT phenomenon because it includes trading activity by investment banks that is not carried out at high frequency.

To solve the endogeneity issue, this study focus on a specific change in technology or market microstructure (the migration of Borsa Italiana's cash markets to the ultra low-latency trading platform, Millennium Exchange) that fostered the HFT participation to the Italian equity market. Millennium is a multi-asset class trading platform, characterized by better technical performances than the previous one. In particular Millennium offers to the market participants the possibility of operating with a lower latency. In fact the migration to Millennium implied a new configuration of Borsa Italiana's servers in order to bring the hardware closer to its markets and ensure greater efficiency and higher speed.

The migration to Millennium allow us to construct a dummy variable taking the value of one in the days after the migration to Millennium and zero otherwise. This dummy can be used as an instrument for HFT activity because it satisfies the exclusion restriction: the instrument is causally related to HFT activity by construction but it is not related to the volatility. Hence through the instrument it can be identified the direction of the causal link between HFT activity and volatility. By applying a instrumental variables fixed effect estimation our results show that an increase of HFT activity on a single stock can be negative for the market quality. In fact an increase of the HFTrs participation to the market causes the stock specific intraday volatility (measured as ten-seconds realized volatility) to increase too.

In all the model specifications used, the impact of HFT activity on volatility is positive and highly significant for both the proxies of HFT activity used (small and large). Moreover, the impact of HFT seems to be higher than the impact of other variables able to affect volatility and used as controls.

We find that an increase by 1 standard deviation of HFT activity carried out by 'pure' HFT firms causes the stock price intraday realized volatility to increase by an amount between 0.5 and 0.8 standard deviations. This means that, if HFT activity increases by 10 percentage points the annualized intraday volatility increases by an amount between 4 and 6 points depending on the specification used. If we take into account also the activity carried out by investment banks (taking their activity as a whole), the impact on volatility is slightly lower. In terms of levels, the impact of an increase by 10 percentage points of HFT activity brings to an increase of annualized volatility by an amount between 3 and 5 points.

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Appendix

Table a.1 – Correlation Matrix

Variables	Volatility	HFT activity	Volume	Market cap	Bid/ask spread	Price-to-book value	FTSE MIB volatility	Millennium	Exchange rate (eur/usd)	3-months Euribor	Btp-Bund spread	Inverse of price	Fragmentation index
Volatility	1												
HFT activity	0.0466	1											
Volume	0.0985	-0.0349	1										
Market cap	0.2567	0.0320	-0.0084	1									
Bid/ask spread	0.3035	-0.2565	0.0391	-0.0551	1								
Price-to-book value	0.2690	0.0265	-0.0062	0.9563	-0.0536	1							
FTSE MIB volatility	0.1217	0.0138	-0.0035	-0.0340	0.0434	-0.0353	1						
Millennium	-0.1410	0.4489	-0.0981	0.0349	-0.6167	0.0134	0.0218	1					
Exchange rate (eur/usd)	-0.1226	-0.2767	0.0756	0.1015	0.0863	0.1230	-0.0684	-0.4910	1				
3-months Euribor	0.1824	-0.4645	0.0898	-0.0317	0.5571	-0.0071	0.0063	-0.9057	0.6222	1			
Btp-Bund spread	0.4296	0.0756	-0.0224	-0.1779	0.3934	-0.1942	0.1503	0.0163	-0.6407	-0.0202	1		
Inverse of price	-0.1934	-0.1022	0.0250	-0.4422	0.0524	-0.4897	0.0265	0.0255	-0.1198	-0.0274	0.1642	1	
Fragmentation index	0.0707	0.2993	-0.0210	-0.0929	-0.0282	-0.1426	0.0110	0.0114	0.0350	-0.0014	-0.0159	-0.2318	1

Table a.2 – The impact of HFT activity on 1-minute stock intraday volatility in the dynamic model

dependent variable: realized volatility (1-minute)	Model 1L		Model 2L		Model 3L		Model 4L		Model 5L	
proxy for HFT activity	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*
HFT activity	0.452***	0.360***	0.555***	0.449***	0.703***	0.559**	0.680***	0.529***	0.768***	0.748***
	[0.002]	[0.000]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.006]	[0.009]
market cap			-0.138***	-0.149***	-0.147***	-0.160***	-0.127***	-0.129***	-0.113***	-0.083**
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.021]
bid/ask spread					0.039***	0.035**	0.036**	0.032**	0.041***	0.046**
					[0.008]	[0.036]	[0.011]	[0.046]	[0.009]	[0.041]
inverse of price							0.406**	0.642***	0.277*	0.330**
							[0.017]	[0.002]	[0.090]	[0.045]
fragmentation index									-0.133**	-0.424**
									[0.014]	[0.014]
FTSE MIB volatility	0.043***	0.031***	0.040***	0.026***	0.039***	0.021**	0.040***	0.023**	0.042***	0.024***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.022]	[0.000]	[0.011]	[0.000]	[0.010]
3-months Euribor	0.382***	0.315***	0.431***	0.352***	0.489***	0.385***	0.483***	0.381***	0.526***	0.477***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Btp-Bund spread	0.218***	0.211***	0.149***	0.135***	0.120**	0.104**	0.112**	0.092*	0.111**	0.082
	[0.000]	[0.000]	[0.001]	[0.003]	[0.026]	[0.046]	[0.032]	[0.051]	[0.050]	[0.165]
Lag (1) volatility	0.491***	0.484***	0.463***	0.451***	0.460***	0.446***	0.458***	0.444***	0.463***	0.453***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
F-statistic (IInd stage)	197.58	197.71	149.30	164.66	109.34	120.62	98.63	130.14	86.42	117.76
Partial F-statistic (Ist stage)	11.57	19.10	10.79	16.66	10.93	13.61	11.33	13.19	8.71	8.56
N. of observations (total)	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460

*, **, *** indicate a significance level of 90%, 95% and 99%, respectively.

Table a.3 – The impact of HFT activity on 5-minutes stock intraday volatility in the dynamic model

dependent variable: realized volatility (5-minute)	Model 1L		Model 2L		Model 3L		Model 4L		Model 5L	
proxy for HFT activity	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*
HFT activity	0.329***	0.259***	0.423***	0.337***	0.567***	0.443***	0.546***	0.418***	0.634***	0.607**
	[0.008]	[0.004]	[0.008]	[0.005]	[0.003]	[0.002]	[0.003]	[0.002]	[0.009]	[0.014]
market cap			-0.139***	-0.146***	-0.147***	-0.155***	-0.129***	-0.129***	-0.115***	-0.089***
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]
bid/ask spread					0.038***	0.036**	0.036***	0.032**	0.041***	0.045**
					[0.004]	[0.014]	[0.006]	[0.020]	[0.005]	[0.019]
inverse of price							0.381***	0.562***	0.255*	0.293**
							[0.008]	[0.001]	[0.075]	[0.035]
fragmentation index									-0.131***	-0.366**
									[0.004]	[0.013]
FTSE MIB volatility	0.041***	0.032***	0.038***	0.027***	0.037***	0.022***	0.037***	0.024***	0.040***	0.025**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.001]	[0.000]	[0.001]
3-months Euribor	0.334***	0.282***	0.377***	0.312***	0.432***	0.343***	0.427***	0.341***	0.471***	0.423***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Btp-Bund spread	0.187***	0.179***	0.114***	0.101***	0.084*	0.069	0.076*	0.058*	0.076	0.050
	[0.000]	[0.000]	[0.001]	[0.008]	[0.054]	[0.117]	[0.068]	[0.146]	[0.101]	[0.328]
Lag (1) volatility	0.462***	0.462***	0.438***	0.435***	0.439***	0.436***	0.435***	0.431***	0.440***	0.441***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
F-statistic (II[nd] stage)	212.28	202.62	187.34	189.79	135.92	138.17	122.76	137.67	112.08	141.89
Partial F-statistic (I[st] stage)	11.69	19.55	11.00	17.37	11.12	14.22	11.50	13.78	8.84	9.03
N. of observations (total)	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460

*, **, *** indicate a significance level of 90%, 95% and 99%, respectively.

Table a.4 – The impact of HFT activity on 10-minutes stock intraday volatility in the dynamic model

dependent variable: realized volatility (10-minute)	Model 1L		Model 2L		Model 3L		Model 4L		Model 5L	
proxy for HFT activity	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*	*small*	*large*
HFT activity	0.275**	0.217**	0.367**	0.292**	0.523***	0.408***	0.502***	0.384***	0.590**	0.566**
	[0.019]	[0.014]	[0.017]	[0.014]	[0.005]	[0.003]	[0.005]	[0.005]	[0.012]	[0.019]
market cap			-0.142***	-0.148***	-0.150***	-0.158***	-0.133***	-0.132***	-0.119***	-0.095***
			[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
bid/ask spread					0.042***	0.039***	0.040***	0.036***	0.045***	0.048***
					[0.002]	[0.006]	[0.003]	[0.009]	[0.002]	[0.009]
inverse of price							0.368***	0.535***	0.244*	0.280**
							[0.006]	[0.002]	[0.072]	[0.034]
fragmentation index									-0.130***	-0.349**
									[0.003]	[0.015]
FTSE MIB volatility	0.042***	0.035***	0.039***	0.029***	0.038***	0.024***	0.038***	0.026***	0.041***	0.027***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.001]
3-months Euribor	0.313***	0.270***	0.355***	0.299***	0.413***	0.331***	0.408***	0.329***	0.452***	0.408***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Btp-Bund spread	0.191***	0.185***	0.115***	0.104***	0.082**	0.068	0.075*	0.059	0.075*	0.051
	[0.000]	[0.000]	[0.001]	[0.004]	[0.046]	[0.107]	[0.059]	[0.137]	[0.091]	[0.307]
Lag (1) volatility	0.415***	0.414***	0.392***	0.390***	0.395***	0.391***	0.392***	0.387***	0.396***	0.395***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
F-statistic (IInd stage)	206.50	199.12	193.47	189.45	143.30	137.45	127.26	133.86	121.45	159.87
Partial F-statistic (Ist stage)	11.68	19.53	11.05	17.43	11.16	14.27	11.57	13.87	8.88	9.04
N. of observations (total)	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460	26,460

*, **, *** indicate a significance level of 90%, 95% and 99%, respectively.