The Backstage of Real-Time Streaming from Exchanges: Technological or Human Latency?[1]

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Abstract

This paper goes beyond the general assumption of reliability of high-frequency market data and investigates delays of a real-time data streaming. Speed and capacity conditions of trading systems are commonly considered attributes that are exogenous and stable, respect to the trading process, mainly depending on technological infrastructures (i.e., "technological" latency). Conversely, speed and capacity are largely influenced by the trading flow itself, and they might vary, also significantly, from time to time.

This paper describes an experiment of an in-house data warehouse constructed in 2008 and 2009, from the real-time streaming provided by a global player to a "geographically-distant" receiving server. By exploiting an optimal condition, in terms of telecommunications networks, we report experience for time-varying conditions of latency. We show that variations of these conditions are due to the overall trading process, mostly related to investors' behavior, thus introducing the idea of a "human" latency. Realized volatility is a "universal" feature of the trading flow that consistently affect the effective latency for the six Stock Exchange analysed. Increase in the volatility of a stock intensifies the effective latency for a "geographically-distant" random trader. Market microstructure may play a role in controlling the effective latency risk.

Keywords: technological latency; human latency; electronic trading; high-frequency market data

I. Introduction

Fast is good, *more* is better. Technological developments of capital markets have been enforcing these broad concepts at the best. Electronic order books allow continuous interactions of orders, competing for exploitation of information which is not uncompounded in prices, yet. Trading process becomes the natural arena of competition among investors, which aim at either using information, or capturing information from others.

Speed and capacity conditions of trading systems are levers of competition of modern capital markets, in a liberal regulatory context. Both in the US and in Europe, regulation allows trading facilities to substitute regulated Exchanges, as in various forms of alternative venues (e.g., multilateral trading facilities, systematic internalizers, dark pools..). This competition has been originally thought to improve fairness and efficiency of securities marketplace; nevertheless it ended up in intensifying technological investments of trading venues that are continuously asked, by market participants, to improve the *speed* (i.e. the "fast") and the *capacity* (i.e. the "more") of their trading platform. Technological innovation largely supported infrastructure upgrades, with enhanced computer power in data storage and processing, as well as the growth of high-performance telecommunications networks, such as Multiprotocol Label Switching (MPLS), Wide Area Networks (WAN).

This paper sits within a variegated literature. From seminal financial economics literature, we consider the real-time trading process as a source of information itself, with implications on asymmetric information and adverse selection costs, as from Kyle, 1985; Glosten and Milgrom, 1985; Easley, O'Hara, 1987; Aslan, Easley, Hvidkjaer, O'Hara, 2011. From engineering and intelligent system literature (e.g. Kulkarni P. 2012), and in relation to the importance of the real-time trading process, we also assume that each trader, both human and not-human, follow an information-decision-action process, based on a reinforcement-learning scenario. The latency of a trading venue is the speed of sending messages to it and receiving back updated information (Hasbrouck and Saar (2013). Latency represents a competitive advantage that induces struggles among both trading venues and traders; it also brings about a renewed interest, in the financial economic literature, for evaluating the effect of technology on market quality and fairness, with still an ongoing debate (Hasbrouck and Saar, 2013; Menkveld and Zoican, 2014).

According to this outstanding literature, speed and capacity conditions of a trading system are commonly assumed attributes *exogenous* and *stable,* respect to the trading process, mainly depending on technological infrastructures. These attributes indicate a *technological latency*. As an example, co-location services offered by Exchanges respond to the need of reducing any form of physical barrier that might interfere with flows of electronic trading.

This paper goes beyond the *technological* meaning of latency, and investigates delays of the real-time data streaming that is practically delivered by Stock Exchanges. We investigate if the latency of a trading system is really *exogenous* and *stable,* or if it is influenced by the trading flow itself.

In order to find evidence of a likely time-varying latency, and to uncover the causes of its variation, this paper describes an experiment of an in-house data warehouse constructed from the real-time streaming provided by a global player to a "geographically-distant" receiving server, during the period 2008 and 2009.

By exploiting an optimal condition in terms of telecommunications networks, we report experience for time-varying conditions of the speed of the data feed received by our random-geographically placed server. These speed variations are related to the trading process, and mainly due to investors' behavior. This indicates that conditions of *technological latency* are often altered by conditions of *human latency*.

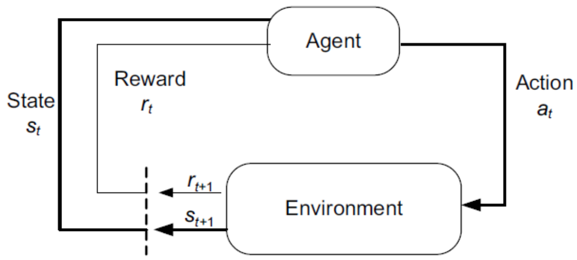
II. Trading Process and Latency

Trading process held in electronic order books has been largely considered the informational input for short terms investment strategies. Adverse selection issues arises when not-informed traders deal with informed investors, and the financial literature largely investigates the behavior of market makers that are asked to trade even if they are not-informed. Asymmetric information among market participants is one of the most agreed theoretical paradigm in market microstructure (Kyle, 1985; Glosten and Milgrom, 1985). Further literature focuses on probability of the informed trading conditional on the trading process (Easley, López de Prado, O'Hara, 2012; Andersen, Bondarenko, 2013).

Recently, the development of AT and HF trading introduced the idea that market (passive) orders placed by HF traders transform these participants into market makers (Menkveld, 2013). "*HF market makers generally do not make directional bets, but rather strive to earn tiny margins on large numbers of trades*." (Easley, López de Prado, O'Hara, 2012, p.1458). This trading strategy generates a position risk, related to the adverse selection problem that arises when a market maker sets passive orders against informed traders[2]

If the trading process is the informational input for trading strategies, it derives that traders and Stock Exchanges/trading venues are theoretically interconnected based on a learning process of information-decision-action, where information observed from the trading process is used to take decisions, either by humans or by machine (AT and HF traders), as described in Figure 1.

Figure 1- Reinforcement-learning scenario



Source: Kulkarni P. (2012) Reinforcement and Systemic Machine Learning for Decision Making, p.16

An Agent (i.e a trader) tends to follow a reinforcement-learning scenario where, from observation of the *Environment* at time t (here the marked data of a Stock Exchange), she assumes a *State* s_t, mainly related to the experience of *Reward* r_t; she processes this information and elaborates an *Action* a_t, that is going to change the *Environment* itself (in our case, the trading process, in terms of limit/market orders and trades). *Action* a_t is going to definitively alter the *Environment*, that generates a new set of conditions in terms of *State* s_{t+1} and *Reward* r_{t+1}.

[2] Such a specific condition has been defined "flow toxicity", and has been estimated with the volume-synchronized probability of informed trading (VPIN, Easley, López de Prado, O'Hara, 2012). Even if the VPIN approach is still largely debated (e.g. Andersen, Bondarenko, 2013), it confirms that quote and trade data, in terms of prices and volumes, is essential to deduce the presence of information in stock markets.

The elapse of time it takes the Environment to update the set of conditions, *s* and *r*, in Figure 1 is simply indicated as a "+1" (from *t* to *t+1*). Nonetheless, this delay is the issue of this paper. Moving from the engineering and intelligent system literature to financial literature, this elapse of time takes the name of "latency", as in Hasbrouck and Saar (2013, p1): " *the time it takes to learn about an event (e.g., a change in the bid), generate a response, and have the exchange act on the response. Exchanges have been investing heavily in upgrading their systems to reduce the time it takes to send information to customers, as well as to accept and handle customers' orders*."

Technological innovation and infrastructure investments radically changed the trading marketplace and several papers observed the effect of technology on market quality. Some of them consider situations of technology failures, such as in relation to crashes, as in Andersen and Bondarenko (2014), but most of the studies analyse technology upgrades. An abundant literature refers to NYSE. For example, Easley, Hendershott and Ramadorai (2014) find significant impacts of technological upgrades on liquidity, turnover, and returns, from the NYSE computer improvements of early 1980's. Hendershott and Moulton (2011) observe the introduction of NYSE Hybrid market, that reduced the execution time for market orders from 10 seconds to less than one second. They find that this automation raised bid-ask spreads, due to increased adverse selection, and made prices more efficient. Similarly to this study, Riordan and Storkenmaier (2012) study the impact of a latency reduction for XETRA, the Deutsche Bourse trading system, on liquidity and price discovery. Their findings on bid-ask spread are opposite from Hendershott and Moulton (2011), but they justify this result because the NYSE Hybrid market implied both a latency reduction and further market structure changes.

Theoretically, decrease in latency should improve efficiency of the reinforcement-learning process of Figure 1, allowing agents to update their states and actions closely to any environmental change. This should support expectations for reduction of adverse selection problems among traders (i.e. reduction of bid-ask spread), as well as for lessening of noisy prices, thanks to a faster dissemination of information. Nevertheless, these overall improvements in market quality are reasonably expected if latency conditions were the same for every trader and constant along time. On the contrary, it is manifest that human ability to respond to environmental changes are "physically" lower than machines' one. Hasbrouck and Saar (2013, p.1) define *low-latency strategies*, i.e. high frequency trading, those "*strategies that respond to market events in the millisecond environment*"; this implies that "*computer algorithms respond to each other at a pace 100 times faster than it would take for a human trader to blink*".

Therefore, new sources of asymmetries and adverse selection costs arise, with likely situations of fast traders picking stale quotes of slow investors. This awareness fosters the debate in the literature on the whole effects of AT and HF trading on market quality, again with not-convergent evidence (Hasbrouck and Saar, 2013; Menkveld and Zoican, 2014).

Fairness of trading is an inevitable implication when comparing traders with different speed constraints.

III. The Experiment: Real Time Streaming and Storage of Data

III.a The Data Feed

Stock market data feed has been obtained by Townsend Analytics, a Chicago-based company that introduced technology innovations affecting worldwide financial services industry, since mid '80s. The experiment has been possible thanks to the Townsend Analytics real-time feed (TALFeed), distributed by an Italian broker, IWBank, formerly Investnet spa, based in Milano (Italy).

The "geographically-distant" receiving server was based at the University of Ancona (Italy) and was connected with the Wide Area Network (WAN) of TAL propriety, thanks to a link with a sending server based at Investnet in Milano. Communications with the WAN of TAL was based on the Italian University GARR connection (namely, the Italian Research & Education Network-NREN), which represents in Europe the frontier of telecommunication efficiency. Typical estimates of GARR latency[3] indicate that we carried on an *optimal* experiment, in the perspective of telecommunication systems (i.e. no latency). Description of connections between Stock Exchanges, TAL's WAN and sending/receiving servers is offered in Appendix 1. The two servers in Milano and Ancona have been *dedicated* to the experiment, with no other task except sending and receiving/storing data. Therefore noisy processing delays, generated by different computer tasks, were excluded.

We use a TCP/IP byte-stream protocol to communicate requests, commands and receive data between servers. Estimation of delay due to the hardware processing of this protocol are largely under our time unit, which is the *second*, as also used in similar studies (Garvey and Wu, 2010). Latency of modern connections, also in trading environment, is typically measured in nanoseconds. Therefore, our time unit would appear remarkably large. Nevertheless, we deliberately choose the *second* because our aim is to exclude inclusion of delays due to hardware frictions, or any other (unlikely) delay due to servers interconnections, that are systematically lower than the second. As an example, we estimated that delays due protocol hardware processing and to ensure the final connection to the TAL's WAN vary within the range of 0.012344- 0.001604 seconds[4]. Therefore, any delay in seconds, recorded between the sending and receiving signal, is reasonably motivated by a congestion situated ahead our receiving system, either due to TAL's or Stock Exchanges' servers.

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[3] See: http://www.garr.it/b/eng.

[4] Details are available upon request.

III.b The Delay of the Real-Time Streaming

The Townsend Analytics leadership in trading services allowed us to investigate several Stock Exchanges simultaneously, whose data feed was based on a common permission environment and the same distributive architecture (see Appendix 1). We selected six Stock Exchanges from North America to Europe: the London Stock Exchange (LSE), the Borsa Italiana Stock Exchange (Bit SE), the Deutsche Bourse (XETRA), the Euronext Paris (PAR SE), the NASDAQ and the New York Stock Exchange (NYSE).

Our requests in terms of TCP/IP protocol consisted in prices, volumes and time stamps, for each trade and each best bid-ask quote, recorded by these Stock Exchange, for a selection of stocks. Based on market capitalisation of the whole listed stocks as at the end of June 2008, for each market we sampled 100 shares divided into three categories: large caps – the first 30 stocks in the first quintile of each market capitalization; medium caps –the first 30 stocks of the third quintile; and small caps – the first 40 stocks of the fifth quintile. In this paper, we offer results limited to large caps[5].

The experiment started on July 21st, 2008 and ended the 23rd of September 2009. Data of initial days were used for experimental testing and then discarded. After conventional cleaning procedures, the observed period is from August 4th 2008 until August 14th 2009. We excluded Christmas and major holidays, and also days when the receiving server of Ancona shut down due to incident or planned maintenance. Finally we observed 256 trading days.

For each transaction and quote, we received and recorded the official time stamp of the Stock Exchange as it was recorded by TAL, together with the time stamp of the receiving server, which was synchronized every 15 minute thanks to a network time protocol. By comparing these two time stamps we obtain our measures of delay: the daily mean, the daily median and the daily standard deviation of number of seconds of difference between the official time stamp and the receiving time stamp (*delay_mean*; *delay_median*; *delay_std*). These variables act as proxy for *effective latency*. These delays are latency measures in technical meaning because refer to time elapsing between sending our request via the TCP/IP protocol, obtaining this information from the Stock Exchange via the data vendor, and receiving back the data.

A Stock Exchange generally divulgate its latency performance refereed to technological attributes. For example, NYSE reduced the trading latency from 350 milliseconds in 2007 to 5 milliseconds in 2009 (Menkveld and Zoican, 2014); with the 8.0 release of Xetra, system latency was reduced from 50 milliseconds to 10 milliseconds (Riordan, Storkenmaier, 2012). These conditions of speed can be reasonably exploited by a limited set of market participants, able to exploit slow-latency strategies, i.e. that work within the millisecond environment (Hasbrouck and Saar, 2013). The 'hosting server' and

[5] For further development of the paper we are going to consider del whole set of stocks.

co-location services offered by Stock Exchange are typically addressed to offer technological latency conditions to traders. But these traders are not humans.

Let us assume a random market participant that is located "geographically-distant" from the Stock Exchange servers. This market participant operates, let's say, from Ancona (Italy), and is able to exploit an *optimal* connection with the trading services provider. Delays that this trader experienced during our observation period are shown in Tables 1.a, 1.b, 1c. Each Table reports the effective latency measures (*delay_mean*; *delay_median*; *delay_std*), by day, computed on our sample of large caps, for each Stock Exchange.

From Tables 1a and 1b we observe that daily median levels of delay (*delay_median*) for large caps of European Stock Exchanges are quite always equal to zero (charts in the center of Tables). This means that the effective latency would seem to be under our time unit (the second) and could be considered close to the official technological latency. Conversely, from Table 1.c we note that for large caps of US Stock Exchange we registered: frequently, a median delay of 2 seconds, often, of 1 second, sometimes, of 3 seconds, and seldom, of 0 seconds. It seems that connections with geographically distant Stock Exchanges imply source of friction that frequently causes delay. This would be in line with similar results in the literature, reporting that location still matter, even if they refer to distances within the US boundaries (Garvey and Wu, 2010).

If we move from daily-median to daily-mean values of delays (*delay_mean,* left charts of Tables 1a, 1b, 1c) the situation appears markedly different: we collect evidence of significant delays that sometimes experience data, affecting in the same day a considerable number of stocks of the sample. This evidence is relevant for both European and Us stocks, and it is confirmed by the daily standard deviation of delay (*delay_std,* right charts of Tables 1a, 1b, 1c). Therefore, conclusions based on daily median levels of delay are not reliable because they are clearly motivated by the ability of the 50th centile to underweight outliers.

As a first result of this paper, we have proof that effective latency conditions are not constant over time, with the likely occurrence of delays, sometimes longer than a few seconds.

The distribution of delay outliers along the daily time line (prog) of Tables 1.a, 1.b, 1.c is informative. For all the Stock Exchanges considered, the delay outliers appear concentrated in specific sub-periods. Keeping in mind that we excluded days when either receiving server or connections shut down, the nature of these sub-periods should hold the response for the delay. The significant increase in mean and standard deviation of delay (*delay_mean* and *delay_std)* for all the six Stock Exchanges is situated in the trading week between the 31st-35th day of the observation period. This is the week which goes from the 15th to the 19th of September 2008: the Lehman Brothers collapse.

Table 2 shows, by each Stock Exchange, a comparison of the effective latency (*delay_mean*) recorded in receiving data, on the one hand, with the trend of the annualized *realized volatility* computed on trades (RVt) and averaged for the sampled stocks, on the other. From Table 2 we observe that the two trends appear similar, suggesting the presence of a *rationale* in the emergence of delays of signals. This descriptive evidence motivates the investigation for any influence generated by the trading flow itself, on the latency that is effectively experienced by "geographically-distant" traders.

V. Does the trading flow affect effective latency?

V.I. Data and Models

From tick-by-tick figures of trades and quotes stored in our data ware house[6], we construct daily measures that describe the trading flow, taking into control the market microstructure that has been varying during the observed period. Standard data cleaning procedures have been adopted to check the integrity of the data, and we delete obvious recording errors. We only consider stocks that had at least one hundred transaction per day necessary for some volatility computations; hence our choice of analysing only large caps, in this paper. Therefore, even if for each Stock Exchange we downloaded the largest 30 caps, we only analyse those that fulfil the minim 100 transaction per day cut off. Moreover, from the initial sample by market capitalization on June 2008, we lost some stocks because they delisted during the observation period, due to various reasons (take overs, M&A, etc..). This explains our final dataset of high frequency stock market data, which covers 162 large-caps during 2008 and 2009, for an observation period of 256 trading days.

We set two models in order to explain our measures of effective latency, *delay_mean* (model 1) and *delay_std* (model2), across stocks "i" and time "t" (day), separately estimated by each Stock Exchange:

[1]

$$
\begin{aligned}
delay\_mean_{i,t} = \alpha_i + \sum_{l=1}^{2} a_l delay\_mean_{i,t-l} + b_1 mess\_traff_{i,t} + b_2 trade\_repor_{i,t} \\
+ b_3 qbas_{i,t} + b_4 volatility_{i,t} + b_5 kurt\_vol_{i,t} + b_6 \text{min\_tick\_size\_trades}_{i,t} \\
+ b_7 std\_imbalance_{i,t} + + \sum_{k=1}^{i} c_k dummy_{i,k,t} + u_{i,t}
\end{aligned}
$$

[6] We checked for consistency of our data with Thompson Reuter dataset and we have proof of its reliability.

[2]

$$
\begin{aligned}
delay\_std_{i,t} = \alpha_i + \sum_{l=1}^{2} a_l delay\_std_{i,t-l} + b_1 mess\_traff_{i,t} + b_2 trade\_repor_{i,t} \\
+ b_3 qbas_{i,t} + b_4 volatility_{i,t} + b_5 kurt\_vol_{i,t} + b_6 \text{min\_tick\_size\_trades}_{i,t} \\
+ b_7 std\_imbalance_{i,t} + + \sum_{k=1}^{i} c_k dummy_{i,k,t} + u_{i,t}
\end{aligned}
$$

The first two variables (*mess_traff*$_{it}$ and *trade_repor*$_{it}$) indicate situations of data congestion, when investors tend to increase messages addressed to the Stock Exchange, either directly, or indirectly through alternative venues. The further two variables (*qbas*$_{it}$ and *volatilty*$_{it}$) summarize the informational content of the trading process, also taking into consideration the literature that relates technological issues with adverse selection costs, and finally bid-ask spreads. For all these variables the main idea is that (as for streets and highways) the higher is the congestion of trading (travelling), the higher the likely delay. The first two variables are direct measures of congestion, the second two are indirect ones, due to the effect of information on the trading flow.

The last set of variables (*kurt_vol*$_{it}$, *min_tick_size_trades*$_{it}$ and *std_imbalance*$_{it}$) works as market microstructure control. This is necessary because we estimate the same set of models (model 1 and model2) for all our six Stock Exchanges, that follow different microstructure architectures. Moreover, the observed period was particularly turbulent with various microstructural changes, differently introduced in the Stock Exchanges analysed.

V.II. Explanatory Variables

The *mess_traff*$_{it}$ has been computed as the total number of electronic messages received by each Exchange for each stock of our sample, i.e. trades' signals added to new bid-ask quotes' messages. This variable is similar to the 'electronic message traffic' used by Hendershott, Jones, and Menkveld (2010) as a proxy for algorithmic trading. Hendershott, Jones, and Menkveld (2010) add also the number of cancellations, but unfortunately, we do not have this information. Even if since this 2010 paper the knowledge of algorithmic trading developed noticeably (Jones, 2013), we believe that this variable indicates the data pressure on both servers and connections, thus expecting a positive role on effective latency. Table 2 offers descriptive statistics of our explanatory variables, comparing the initial phase (the core of the crisis) and the final phase based on a more stable period. Concerning the average number of messages, it decreased from the first to the second sub-sample period. The US market are characterized by the largest number of messages (by a factor of 2-3). This could indicate that trading in US markets has a larger component of AT than European markets. Interestingly, the Italian market shows the lowest level of messages (see Table 2). This may indicate a different level of development of Borsa Italiana. In fact, while the number of messages between sub-periods decreases for all market, for the Italian market it increases.

The *trade_repor*$_{it}$ is a proxy of the daily number of trades reported from venues others than the Stock Exchange electronic order book. This phenomenon is a typical consequence of the regulatory allowance for alternative trading venues. This flows of data may cause congestion and we expect a positive effect on effective latency. Table 2 shows that in most of the European Stock Exchanges the median values of this variable are zero, meaning that the activity of venues different from regulated market was not still so developed, compared to US markets that show high values of *trade_repor*$_{it}$. Anyway, this variable for US markets decreased in the second sub-sample.

The *qbas*$_{it}$ is the quoted bid ask spread, computed on a daily basis for each stock. The *volatilty*$_{it}$ is the realized volatility from transactions that has been plotted in Figure 2 and already compared with *dealy_mean*. Following traditional finance literature, this variable represents information and the idiosyncratic drivers of trading. We computed three estimators of realized volatility. The first one is the classic measure of realized volatility developed by ABDL, 2000. To overcome the bias induced by the variance of the noise, we optimally sample realized volatility for every month and every stock, by computing the volatility signature plots. The second measure of realized volatility we adopt is the Kernel estimator of B-NHLS (2009). Finally, we adopt the TSRV of Zhang, Mykland and Aït-Sahalia (2005). All these measures have very similar behaviour and are highly correlated. Results are robust to the different realized volatility measures. For *volatilty*$_{it}$ and *qbas*$_{it}$ we would expect a positive/negative effect on effective latency, because the higher the information available (more volatility) and transparently shared among market participants (low adverse selection and low bid-ask spread), the higher the pressure on sending signals, thus causing likely increase in effective latency.

Then, we consider the market microstructure controls. Given the panel structure of our models, we focused on those variables that could be both different among Stock Exchanges and time-varying. The *kurt_vol*$_{it}$ represents the kurtosis of intraday trading volumes, proxy of specific orders permitted in each market, such as iceberg orders (low values of kurtosis) or block trading (high value of kurtosis). Trading in large quantity may cause a price impact. To avoid this, a Stock Exchange may allow the split of orders in "typical" sizes for that market – i.e. if a typical order is 100 shares, then a larger order will be split in pieces of 100. From Table 2 we have evidence that in the NYSE these measures of kurtosis are higher than in all the other markets (including NASDAQ). Also, these measures decrease from the beginning to the end of our period, indicating that at the highest of the crisis block trading were more frequent.

The *min_tick_size_trades*$_{it}$ represents the *daily percentage of transactions at the minimum tick size*. European Stock Exchanges frequently changed the tick size regime in the observed period as a competitive tool to face the development of alternative trading venues[7]; nevertheless, we realized that market participants gradually reacted to these changes. Harris (1994) assumes that the consequences of a tick size reduction are different for actively or infrequently traded securities. According to his studies, frequently traded securities tend to exploit the benefit from lower tick sizes, at the best. Nevertheless, from Table 2 we have evidence that even if stocks of our sample are large caps, traders of all European Stock Exchanges *do not* trade often at the lowest tick size, with the exception of the LSE. In fact, LSE is the European Exchange most exposed to alternative trading venue competition. We use this variable as a proxy of how traders exploit benefits of change in tick size regimes.

The $std\_imbalance_{it}$ variable represents the daily standard deviation of the intraday order imbalance, as the dollar value of the ask side minus the dollar value of bid side of the order book. We use this variable as proxy for short selling rules. As short selling is precluded, the ask size of the order book is affected, causing a rebalancing of the two sides of the order book; consequently a change in the standard deviation of the imbalance is caused (or should be caused, in relation to how many market participants were effectively asked to attend to the rule). During the period observed many Stock Exchanges applied short selling bans differently, due to the sub-prime crises, as documented in Beber and Pagano (2013). For all Stock Exchanges, these bans were not applied to market makers and some other market participants. This is why we prefer to indirectly measure the effect of the ban in term of variability of the intraday order imbalance.

Finally, $\mathrm{dummy}_{i,k,t}$ represent the list of dummy variables that we included to consider both evident system error on delays, and those days when the receiving server and connection shut down; a_i refers to the stock fixed effect; $u_{i,t}$ is the error term.

We checked for collinearity of these variables. The *delay_mean*, *mess-traff*, *trade-repor*, *volatility* and *kurt_vol* are computed in log.

We are aware that endogeneity problems arise because of the not unambiguous direction of the relationship between our dependent variables (*delay_mean* and *delay_std*) and our direct measure of congestions ($mess\_traff_{it}$ and $trade\_repor_{it}$). Is it the congestion to cause the queue and the delay, or is the queue/delay to cause the congestion? Therefore these first two explanatory variables were instrumented. We use two economically reasonable set of instruments: data of CDS rates Italy vs/US and Germany vs/Us in order to testify the spread of the crisis and its effect on Stock Exchanges, on the one hand; and the first and second order of lags of instrumented variables and of volatility. Nevertheless, from Tables 3 we have evidence that if these instruments are valid in terms of underidentification tests (based on the Kleibergen-Paap rk LM statistic), there are still problems with the overidentification test of all instruments (Hansen J statistic).

[7] We collected from each Stock Exchange web-site the list of any institutional change in the tick size regime, during our observation period. Many changes have been introduced, especially in the European Stock Exchanges, mainly as a competitive strategy to face the ATVs growth. Nevertheless, by checking this information with our dataset we realized that market participants moved to the new tick-size regime only gradually.

VI. Results and conclusion

Results of estimations of model 1 and model 2 are shown in Table 3.a and Table 3.b. Nevertheless, the presence of endogeneity and the (still) not perfectly reliable Hansen J statistics suggest cautiousness in their comments[8].

Nevertheless, robustness checks with alternative estimations suggest three main reliable results, as far as determinants of *delay_mean* (Table 3.a).

Direct measures of congestions, i.e. $mess\_traff_{it}$ and $trade\_repor_{it}$, do not consistently behave as expected in all the Stock Exchanges considered, with a significant role but sometimes opposite signs. Precisely, the $mess\_traff_{it}$ variable indicates a different effect on effective latency, among Stock Exchanges, and we believe that it is due to the different level of AT development in the various markets observed (as shown by Table 2). Conversely, the $trade\_repor_{it}$ consistently play a positive role on *delay_mean*, as expected. We discard the Paris results because here the relevance of this external reporting appears limited, as shown by the median value of this variable equals to zero (see table 2).

Indirect measures of pressure, due to the informational content of the trading flow, play a various effect on effective latency, as well. The $qbas_{it}$ appears seldom significant; when it is so, in LSE, NASDAQ and NYSE, the sign is in line with expectations only for the latter. Conversely, $volatilty_{it}$ is always significant and with the expected sign. This is the most important result of the paper: volatility is positively related to effective latency.

As expected, control market microstructure variables show various significance and sign, for the six Stock Exchanges, supporting that it is not possible to generalize, as for volatility, an "universal" driver of effective latency.

Then, we find worthy to comment this latter result with that shown by Table 3.b, referring the relation between *delay_std* and the control microstructure variables. The *delay_std* variable indicates the standard deviation of the delay, recorded within the trades' and quotes' signals of the same stock in the same day. It refers to the effective latency, but it reminds an idea of "latency risk" because it indicates if the delay of the signal is stable (e.g. two seconds), or volatile during the day (e.g. the delay might be 0 as well as 4 seconds). Interestingly, the four direct and indirect measure of congestions never show consistent results, both in significance and sign. Conversely, the variables that control market microstructure appear particularly consistent (see the $kurt\_vol_{it}$ and the $std\_imbalance_{it}$ variable, the latter for the US exchanges) It seems that market microstructure play a role in controlling the effective latency risk.

[8] From Hasbrouk and Saar (2013) we are going to compute further variables to be used as instruments. Nevertheless, their computation, in our dataset, requires a considerable amount of time.

"It reminds me of the old story of the two high frequency traders on safari. Coming out of the jungle into a clearing, they are faced with a hungry lion, staring at them and licking his lips. One of the traders immediately starts taking off his boots and donning a pair of sneakers. "What are you doing?" says the other trader. "You'll never be able to outrun a hungry lion." "I don't need to outrun the lion," says the first trader. "I only need to outrun you."

— HFT Review, April 2010, from Menkveld and Zoican, 2014

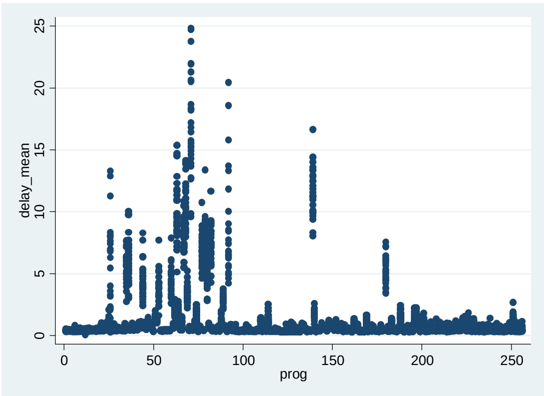
Results of this paper are informative in relation the asymmetry among investors implicitly revealed by the above quoted metaphor. The effective latency is a time varying phenomenon and it is strictly related to the trading flow itself. Geographically distant investors experience an effective latency very different than other traders. Moreover, comparisons among different Stock Exchanges, with different microstructure architecture, different degree of development of computer trading, and likely different investors' trading behaviour, indicate the presence of an "universal" feature of the trading flow that consistently affect the effective latency: volatility. Increase in the volatility of a stock has been proved to positively intensify the effective latency for a "geographically-distant" random trader. Market microstructure may play a role in controlling the effective latency risk.

Table 1.a. Signal delays by Stock Exchange

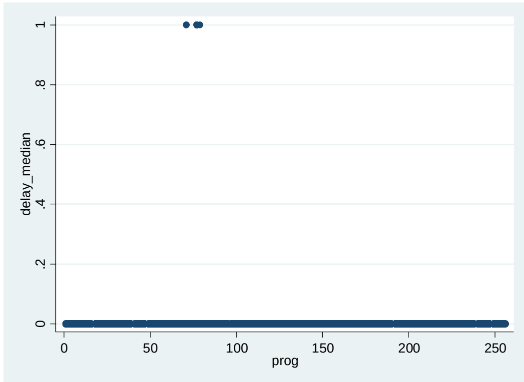
These charts indicate the signal delay experienced by the sample of large cap stock analyzed, during the observed period, by each Stock Exchange considered. Dates are codified by a progressive number: 1: 20080804- 50: 20081010- 100: 20090108- 150: 20090319- 200: 20090528- 250: 20090806. Figures refers to (left charts) the daily mean of the signal delay in number of seconds, registered as the difference between the sending signal, as the time stamp formally included in the data feed, and time stamp of the receiving server; (middle charts) the daily median of the signal delay and (right charts) daily standard deviation of the signal delay. London Stock Exchange- LSE: 28 stocks; Deutsche Bourse-XETRA: 23 stocks. We excluded days when the receiving server of Ancona shut down due to incident or planned maintenance.

London Stock Exchange- LSE

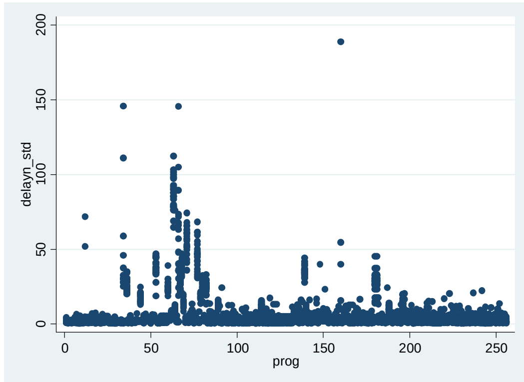
delay_mean



delay_median

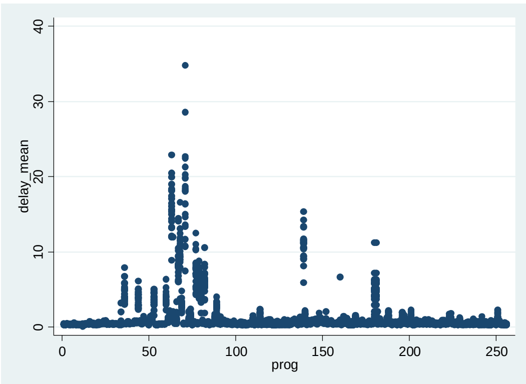


delay_std

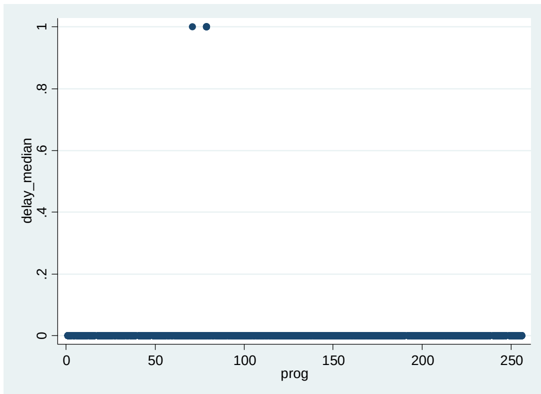


Deutsche Bourse-XETRA

delay_mean



delay_median



delay_std

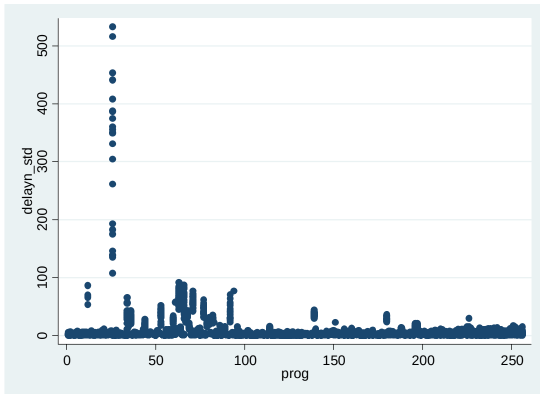
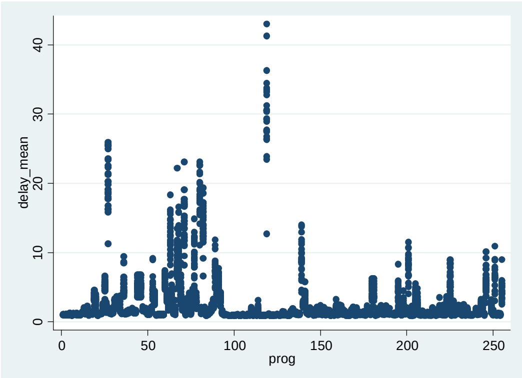


Table 1.b Signal delays by Stock Exchange

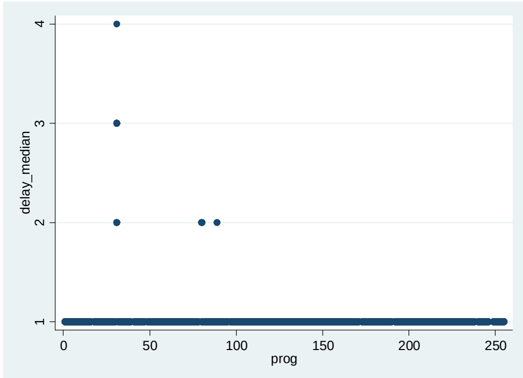
These charts indicate the signal delay experienced by the sample of large cap stock analyzed, during the observed period, by each Stock Exchange considered. Dates are codified by a progressive number (prog): 1: 20080804- 50: 20081010- 100: 20090108- 150: 20090319- 200: 20090528- 250: 20090806. Figures refers to (left charts) the daily mean of the signal delay in number of seconds, registered as the difference between the sending signal, as the time stamp formally included in the data feed, and time stamp of the receiving server; (middle charts) the daily median of the signal delay and (right charts) daily standard deviation of the signal delay. Euronext Paris-PAR: 27 stocks; Borsa Italiana-BIt: 26 stocks; We excluded days when the receiving server of Ancona shut down due to incident or planned maintenance, plus some outliers with abnormal delays (delaymean>50"), precisely, for Paris: 20081120-20090420 -20090814; for Milan: 20081112- 20090427 - 20090303- 20090316).

Euronext Paris-PAR SE

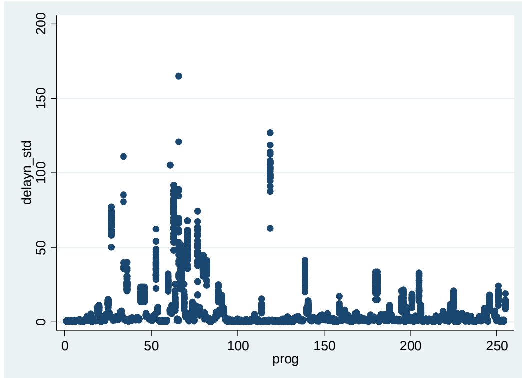
delay_mean



delay_median

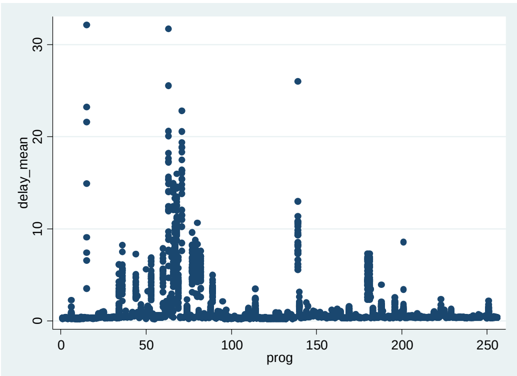


delay_std

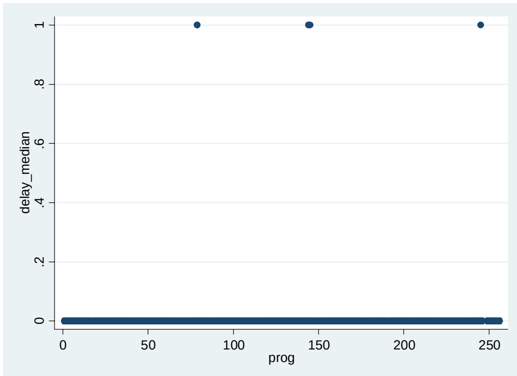


Borsa Italiana-Bit SE

delay_mean



delay_median



delay_std

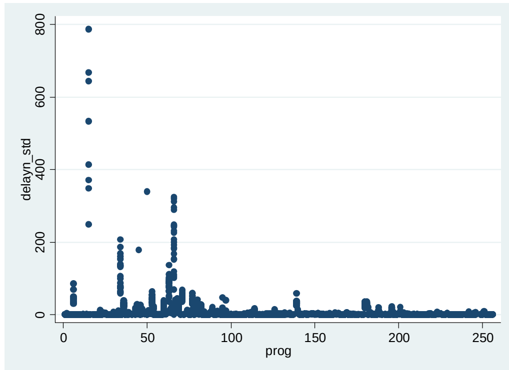
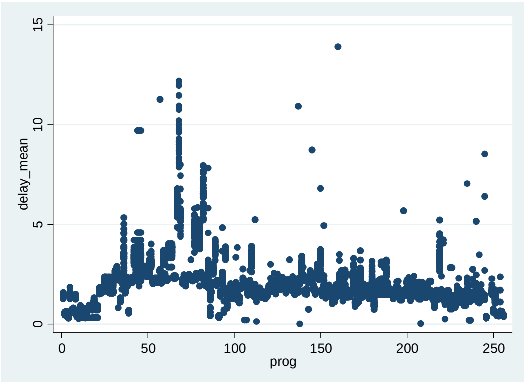


Table 1.c. Signal delays by Stock Exchange

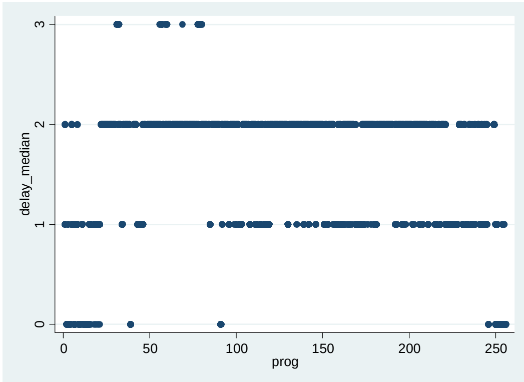
These charts indicate the signal delay experienced by the sample of large cap stock analyzed, during the observed period, by each Stock Exchange considered. Dates are codified by a progressive number (prog): 1: 20080804- 50: 20081010- 100: 20090108- 150: 20090319- 200: 20090528- 250: 20090806. Figures refers to (left charts) the daily mean of the signal delay in number of seconds, registered as the difference between the sending signal, as the time stamp formally included in the data feed, and time stamp of the receiving server; (middle charts) the daily median of the signal delay and (right charts) daily standard deviation of the signal delay. NASDAQ: 30 stocks; NYSE: 28 stocks. We excluded days when the receiving server of Ancona shut down due to incident or planned maintenance.

NASDAQ

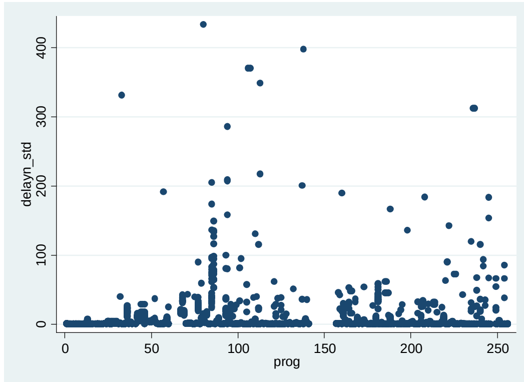
delay_mean



delay_median

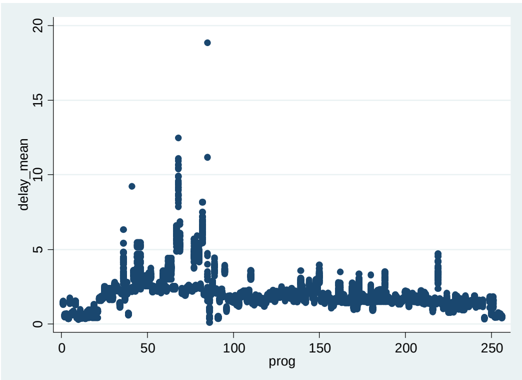


delay_std

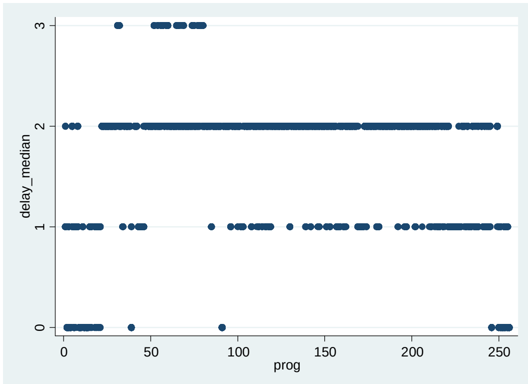


NYSE

delay_mean



delay_median



delay_std

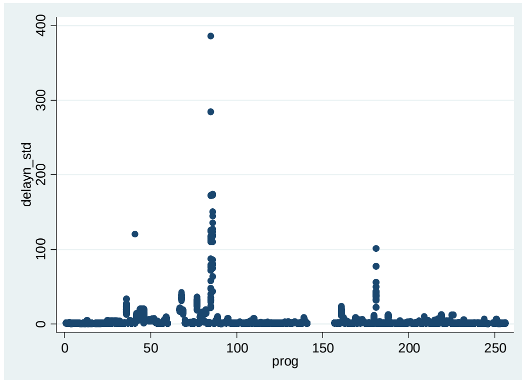
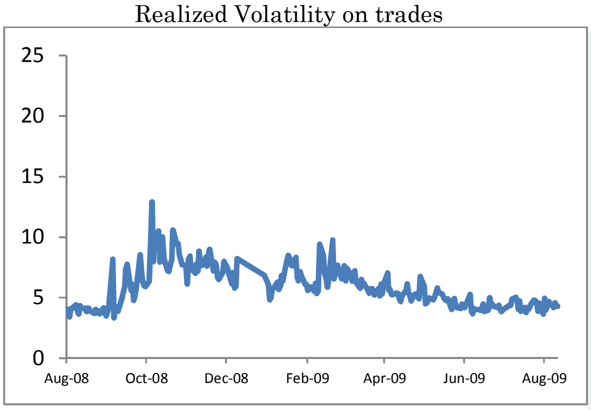


Figure 2: Realized Volatility on trades (RVt) and Effective Latency (delay_mean)

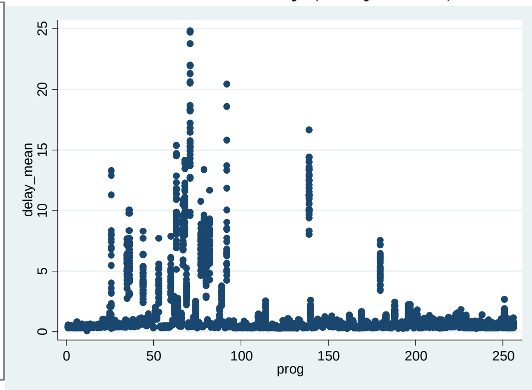
Realized Volatility on trades is annualized standard deviation; daily mean of the delay in seconds between the official time stamp and the receiving server time stamp. Computations refer to the same period and the same sample of stocks, for each Stock Exchange.

London Stock Exchange- LSE

Realized Volatility on trades

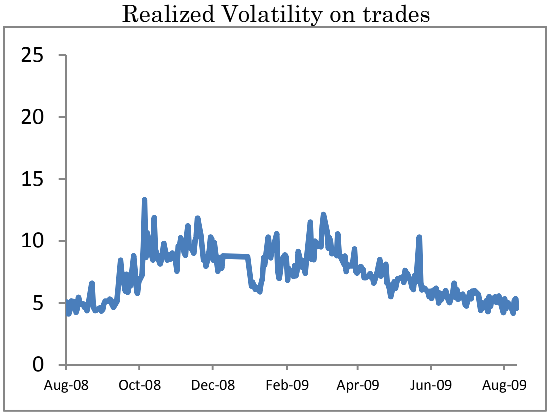


Effective Latency (delay_mean)

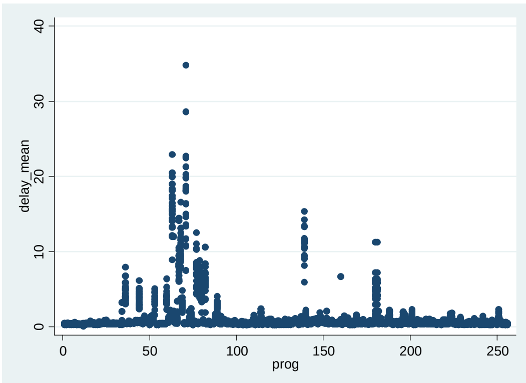


Deutsche Bourse-XETRA

Realized Volatility on trades

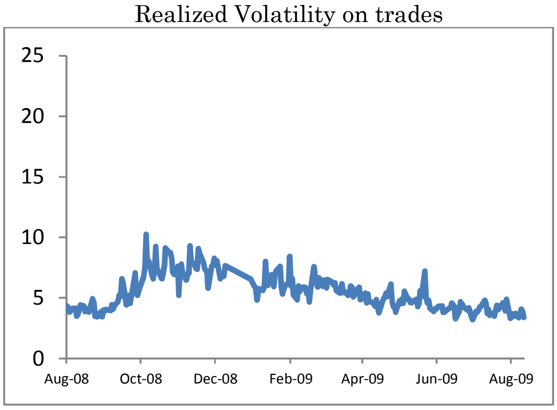


Effective Latency (delay_mean)



Euronext Paris-PAR SE

Realized Volatility on trades



Effective Latency (delay_mean)

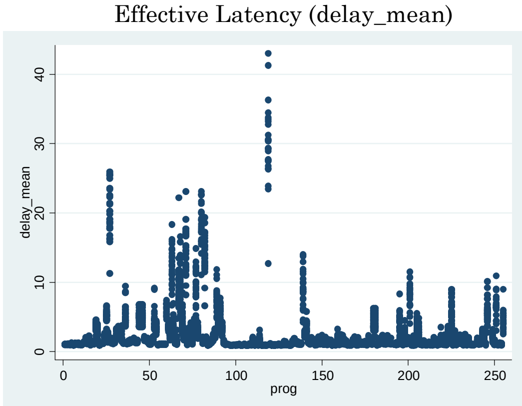
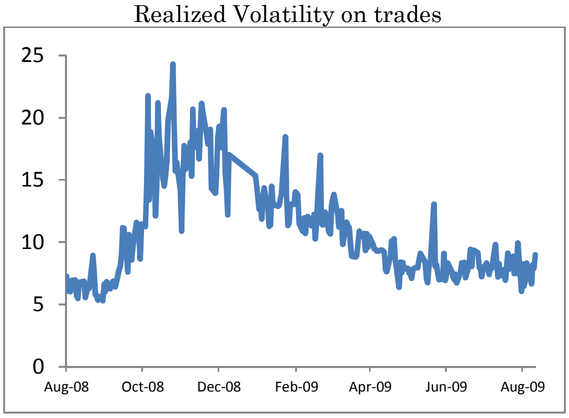


Figure 2: Realized Volatility on trades *continued*

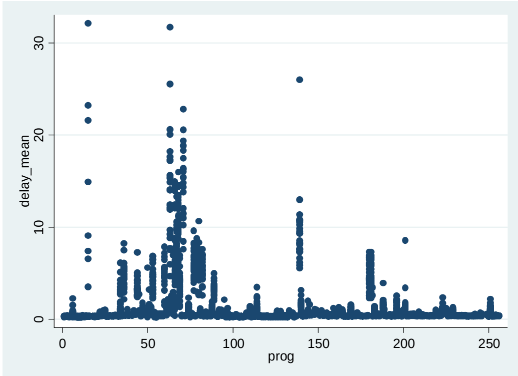
Realized Volatility on trades is annualized standard deviation; daily mean of the delay in seconds between the official time stamp and the receiving server time stamp. Computations refer to the same period and the same sample of stocks, for each Stock Exchange.

Borsa Italiana-Bit SE

Realized Volatility on trades

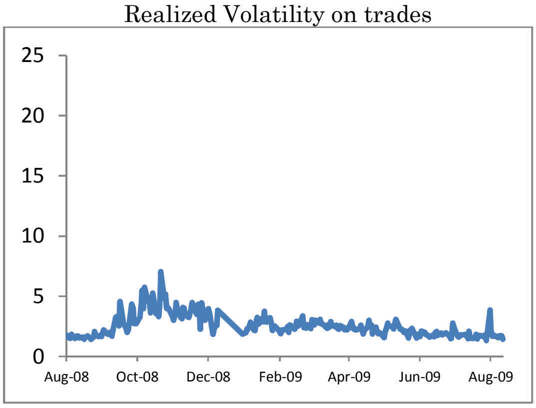


Effective Latency (delay_mean)

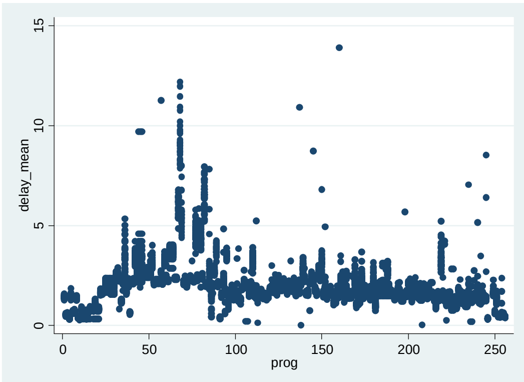


NASDAQ

Realized Volatility on trades

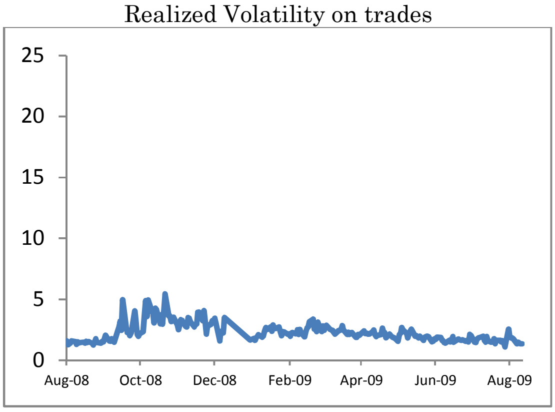


Effective Latency (delay_mean)



NYSE

Realized Volatility on trades



Effective Latency (delay_mean)

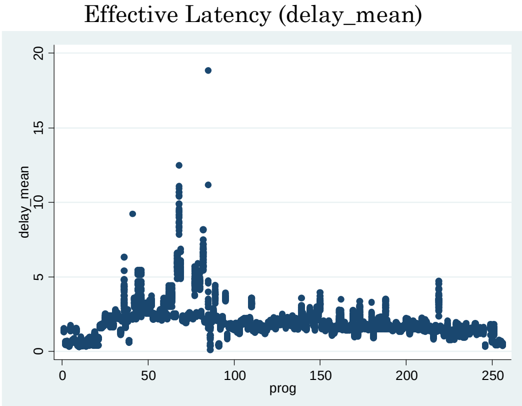


Table 2- Descriptive statistics for explanatory variables

Median values of descriptive statistics by stock market: London Stock Exchange- LSE: 28 stocks; Borsa Italiana-BIt: 26 stocks; Deutsche Bourse-XETRA: 23 stocks; Euronext Paris-PAR: 27 stocks; NASDAQ: 30 stocks; NYSE: 28 stocks. First Sub-Period: August 4th 2008 – February 13th 2009 (126 days). Second Sub-Period: February 16th 2009 - August 14th 2009 (130 days).

	First Sub-Period					Second Sub-Period				
LSE	**median**	**mean**	**std.dev**	**min**	**max**	**median**	**mean**	**std.dev**	**min**	**max**
mess-traff	48665.75	48842.19	18565.01	7066	111241	44434.5	46994.53	12707.84	17653	88008
trade-repor	0	1.444444	4.302948	0	29	0	0.6615385	1.606722	0	13
volatilty	5.4121	5.7857	2.1011	2.3851	13.4172	4.2950	4.4653	1.2159	1.9542	9.3431
kurt_vol	2096.46	3081.26	2882.15	35.03	13983.66	1816.70	2258.37	1934.53	37.39	9115.19
min_tick_size_trades	0.7537	0.7581	0.0896	0.3042	0.9314	0.8373	0.7966	0.0953	0.2173	0.9420
std_imbalance	0.5255	0.5259	0.0191	0.4831	0.5786	0.5325	0.5337	0.0188	0.4898	0.5793
BIt	**median**	**mean**	**std.dev**	**min**	**max**	**median**	**mean**	**std.dev**	**min**	**max**
mess-traff	7279	7670.468	3224.369	2037.5	19036.5	11536.25	12710.29	5062.1	3383	34151
trade-repor	0	0.7777778	2.00899	0	13.5	0	0.5461538	1.302321	0	9
volatilty	10.4928	11.3330	5.4852	3.1142	28.6774	7.5031	8.1242	2.9150	2.8005	19.4577
kurt_vol	53.10	368.23	869.77	8.99	4989.81	50.78	253.40	535.76	10.71	3307.34
min_tick_size_trades	0.3377	0.3684	0.1729	0.0040	0.7446	0.3824	0.4113	0.1673	0.0044	0.7546
std_imbalance	0.5654	0.5662	0.0294	0.4935	0.6411	0.5496	0.5494	0.0249	0.4755	0.6207
XETRA	**median**	**mean**	**std.dev**	**min**	**max**	**median**	**mean**	**std.dev**	**min**	**max**
mess-traff	53981.5	56337.7	26694.8	15046	143228	44594.5	49904	13728.14	10027	89296
trade-repor	22	26.18254	19.54949	3	115	17.5	21.04615	13.26992	0	79
volatilty	5.5683	5.8569	2.3774	2.0102	15.7237	5.2649	5.4767	1.8805	1.9133	12.7263
kurt_vol	1194.99	2156.94	2565.82	21.07	13519.35	990.07	1538.09	1610.86	19.31	6808.18
min_tick_size_trades	0.2858	0.2761	0.0861	0.0059	0.4455	0.3055	0.3005	0.0720	0.0344	0.4551
std_imbalance	0.5361	0.5368	0.0193	0.4948	0.5967	0.5336	0.5345	0.0162	0.4928	0.5916
PAR	**median**	**mean**	**std.dev**	**min**	**max**	**median**	**mean**	**std.dev**	**min**	**max**
mess-traff	47603.5	52011.9	23455.32	12370	123493	47765	51067.48	14879.2	12093	98619
trade-repor	0	4.809524	37.02512	0	414	0	0.9	2.127159	0	16
volatilty	5.4974	5.7333	2.1151	2.2230	12.0622	4.1724	4.3403	1.3475	1.6437	9.5741
kurt_vol	201.00	1193.50	2392.93	20.32	13473.81	185.47	779.27	1621.74	22.48	9421.24
min_tick_size_trades	0.1718	0.1731	0.0803	0.0476	0.4298	0.1449	0.1581	0.0704	0.0090	0.3659
std_imbalance	0.5297	0.5305	0.0214	0.4774	0.5899	0.5170	0.5169	0.0243	0.4554	0.5814
NASDAQ	**median**	**mean**	**std.dev**	**min**	**max**	**median**	**mean**	**std.dev**	**min**	**max**
mess-traff	102489.8	105911.6	30950.25	41888	250557.5	94858.75	97226.36	30425.08	18287	229043.5
trade-repor	991.75	1093	764.7558	0	3271.5	675	711.7769	391.1554	3	2262.5
volatilty	2.3584	2.6153	1.2253	0.9510	7.2577	1.9972	2.0760	0.6175	0.8335	4.6671
kurt_vol	4531.41	8463.89	9268.52	159.89	43304.34	4484.03	7906.66	8673.98	224.02	42329.56
min_tick_size_trades	0.3992	0.4094	0.1207	0.0261	0.6602	0.4333	0.4807	0.0904	0.1014	0.6894
std_imbalance	0.4695	0.4712	0.0256	0.4093	0.5361	0.4610	0.4597	0.0255	0.3879	0.5220
NYS	**median**	**mean**	**std.dev**	**min**	**max**	**median**	**mean**	**std.dev**	**min**	**max**
mess-traff	143496	155715.6	48623.49	64681.5	357664	115466.8	126744.3	44086.12	24435	258543.5
trade-repor	1929.25	2004.766	1374.755	0	5422.5	1349.75	1376.893	683.3293	3	3614.5
volatilty	1.9691	2.1977	0.9955	0.8613	6.7834	1.8098	1.8166	0.5922	0.6844	3.7500
kurt_vol	11283.09	17155.19	14956.11	528.58	70419.43	8919.50	14968.84	13888.04	331.33	83474.05
min_tick_size_trades	0.4135	0.4339	0.1083	0.0701	0.6781	0.5905	0.5755	0.0358	0.3565	0.7053
std_imbalance	0.4937	0.4922	0.0258	0.4322	0.5538	0.4836	0.4861	0.0198	0.4233	0.5343

Table 3.a- Estimates results (*preliminary*)

IV (2SLS) estimations. Statistics robust to heteroskedasticity and clustering on stock. Dependent variable: *delay_mean*

	LSE			XETRA			Bit SE			PARIS SE			NASDAQ			NYSE		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
L1.delay_mean	0.1794	0.0116	***	0.2097	0.0063	***	0.1118	0.0140	***	0.2361	0.0088	***	0.1500	0.0182	***	0.1855	0.0130	***
L2.delay_mean	0.0786	0.0090	***	0.0949	0.0109	***	0.0974	0.0049	***	0.0966	0.0051	***	0.1301	0.0069	***	0.1674	0.0074	***
mess-traff	0.0712	0.0382	*	0.0258	0.0281		-0.0696	0.0233	***	0.0821	0.0199	***	-0.0917	0.0205	***	0.0375	0.0149	**
trade-repor	0.4075	0.0505	***	0.1476	0.0223	***	0.8017	0.1216	***	-0.0398	0.0430		0.1984	0.0111	***	0.1543	0.0097	***
qbas	0.6547	0.2541	**	0.2338	0.2094		0.1091	0.1875		0.1510	0.1047		0.9190	0.2495	***	-0.3041	0.1593	*
volatilty	0.1918	0.0448	***	0.2229	0.0362	***	0.0272	0.0360		0.1089	0.0186	***	0.1661	0.0194	***	0.1420	0.0223	***
kurt_vol	0.0162	0.0073	**	0.0061	0.0043		-0.0089	0.0094		0.0585	0.0091	***	-0.0025	0.0036		-0.0339	0.0057	***
min_tick_size_trades	-0.0560	0.0529		0.1909	0.0763	**	-0.1360	0.0613	**	-0.0078	0.0707		-0.0815	0.0346	**	-0.1134	0.0472	**
std_imbalance	0.00004	0.00002	***	-0.0001	0.0010		0.0029	0.0013	**	0.0032	0.0025		-0.0018	0.0007	**	-0.00002	0.00047	
dummy 1	0.4686	0.1929	**	-0.4557	0.1100	***	-0.1693	0.1508		-0.3725	0.1432	***	0.1439	0.1451		-0.0106	0.0586	
dummy 2	-0.2461	0.0170	***	-0.1740	0.0193	***	-0.2243	0.0227	***	-0.1657	0.0180	***	0.2968	0.0312	***	0.3752	0.0154	***
dummy 3							5.9388	0.2403	***	3.2062	0.1341	***						
α	-1.7892	0.4152	***	-1.6461	0.3244	***	-0.1261	0.2603		-1.0563	0.2408	***	0.0594	0.2195		-0.8946	0.1672	***
Number of obs	*6705*			*5627*			*5976*			*5689*			*6697*			*6360*		
Number of clusters (stock)	*27*			*23*			*24*			*24*			*28*			*26*		
F(11, 26)	*1308.59*			*927.14*			*839.93*			*3614.54*			*727.68*			*2435.64*		
Prob > F	*0*			*0*			*0*			*0*			*0*			*0*		
Centered R2	*0.382*			*0.1799*			*0.6449*			*0.317*			*0.5942*			*0.5831*		
UnCentered R2	*0.5675*			*0.4765*			*0.708*			*0.5416*			*0.7888*			*0.8022*		
Residual SS	*2710.872*			*2776.55*			*3003.06308*			*2244.271343*			*835.585995*			*757.09461*		
Root MSE	*0.6359*			*0.7024*			*0.7089*			*0.6281*			*0.3532*			*0.345*		
Kleibergen-Paap rk LM statistic	*26.703*			*19.204*			*22.444*			*22.406*			*27.427*			*25.596*		
Chi-sq(10) P-val	*0.0029*			*0.0378*			*0.013*			*0.0132*			*0.0022*			*0.0043*		
Hansen J statistic	*26.255*			*22.155*			*22.302*			*21.599*			*26.354*			*25.675*		
Chi-sq(9) P-val	*0.0019*			*0.0084*			*0.008*			*0.0102*			*0.0018*			*0.0023*		

Table 3.b- Estimates results (*preliminary*)

IV (2SLS) estimations. Statistics robust to heteroskedasticity and clustering on stock. Dependent variable: *delay_std*

	LSE			XETRA			Bit SE			PARIS SE			NASDAQ			NYSE		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
L1.delay_mean	0.0123	0.0026	***	0.1282	0.0361	***	-0.0013	0.0013		0.0103	0.0067		0.6109	0.0056	***	0.6248	0.0047	***
L2.delay_mean	0.0122	0.0032	***	0.0436	0.0220	**	0.0037	0.0007	***	-0.0044	0.0063		-0.2956	0.0056	***	-0.3167	0.0025	***
mess-traff	1.6622	0.9673	*	0.3528	0.4355		-51.3543	7.6188	***	2.0786	0.5371	***	-17.2780	3.4059	***	-14.8758	2.7199	***
trade-repor	2.5083	1.5991		1.7039	0.2882	***	93.6725	26.4929	***	7.3714	1.2206	***	-4.7893	0.9820	***	-4.1436	1.0229	***
qbas	1.7638	8.5240		5.2267	3.0309	*	-209.9562	95.5085	**	5.2619	2.8123	*	27.3266	27.0919		43.3137	18.4634	**
volatilty	3.6070	1.3154	***	2.8127	0.5425	***	-48.7879	10.0499	***	1.8099	0.4498	***	3.3650	2.2020		-2.1371	1.6623	
kurt_vol	0.3144	0.1343	**	0.1771	0.0656	***	-1.8268	4.1821		0.4612	0.1745	***	4.8251	0.6146	***	4.4076	0.5594	***
min_tick_size_trades	-0.2711	0.8445		2.3784	1.3221	*	-24.8696	33.2227		2.6546	1.6985		1.1928	4.4490		-4.1342	6.2776	
std_imbalance	0.0001	0.0001		-0.0090	0.0149		1.1638	0.8459		-0.0702	0.0965		0.3966	0.1531	**	0.0555	0.0220	**
dummy 1	79.4832	23.8589	***	-5.7424	0.9126	***	19.4223	15.7448		-4.8201	3.6733		52.7224	31.5942	*	1.4946	6.5109	
dummy 2	-2.5628	0.4216	***	-0.4656	0.5612		-20.6940	5.2020	***	-2.7001	0.3966	***	41.2484	2.6457	***	41.0124	3.5418	***
dummy 3							4051.4320	143.4640	***	136.1175	9.4554	***						
α	-21.3251	10.7730	**	-12.3248	4.8606	**	597.5697	86.2549	***	-25.7353	6.0768	***	182.8079	33.3475	***	168.5346	28.9593	***
Number of obs	*6723*			*5723*			*5976*			*5757*			*6972*			*6474*		
Number of clusters (stock)	*27*			*23*			*24*			*24*			*28*			*26*		
F(11, 26)	*30.3*			*107.58*			*253.39*			*951.82*			*2370.2*			*13053.37*		
Prob > F	*0*			*0*			*0*			*0*			*0*			*0*		
Centered R2	*0.1417*			*0.0837*			*0.5862*			*0.5037*			*0.3702*			*0.3699*		
UnCentered R2	*0.2103*			*0.2368*			*0.5908*			*0.5549*			*0.3831*			*0.3791*		
Residual SS	*2550521*			*638485.5*			*1096414138*			*1422632.272*			*31531113.6*			*27908581*		
Root MSE	*19.48*			*10.56*			*428.3*			*15.72*			*67.25*			*65.66*		
Kleibergen-Paap rk LM statistic	*26.68*			*20.08*			*22.852*			*22.408*			*27.461*			*25.065*		
Chi-sq(10) P-val	*0.0029*			*0.0285*			*0.0113*			*0.0132*			*0.0022*			*0.0052*		
Hansen J statistic	*25.726*			*20.761*			*22.558*			*21.734*			*25.175*			*21.687*		
Chi-sq(9) P-val	*0.0023*			*0.0138*			*0.0073*			*0.0098*			*0.0028*			*0.0099*		

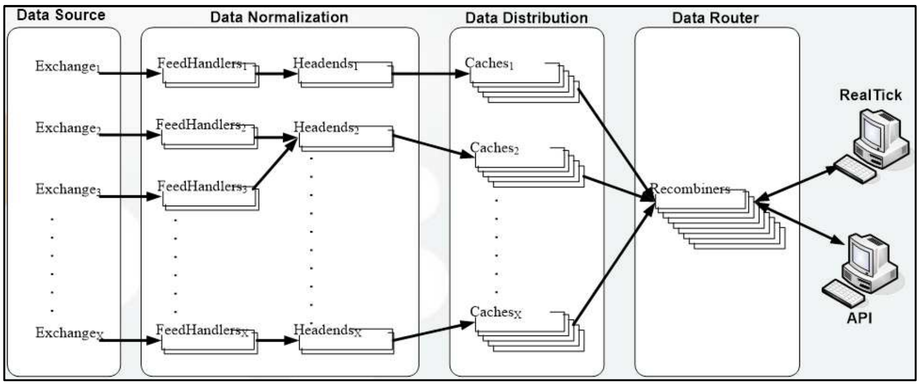
Appendix 1: The real- time streaming of market data

The real-time streaming of market data was possible thanks to an agreement with Investnet Italia. In 2008 this company was the Italian data vendor for Realtick©, a trading platform developed and offered by Townsend Analytics, Ltd. (TAL). The period of the streaming is from 24-06-2008 to 31-10-2009.

Townsend Analytics is a Chicago-based company specialized in technology innovations for trading, since 1985. Among the most relevant services, we quote: the first real-time financial software under Microsoft Windows®; the first product to provide real-time streaming data over the Internet; the first integrated solution for NASDAQ trading rooms; and the first Windows-based direct-access trading solution. Townsend Analytics also developed Archipelago and the Archipelago Exchange, the first US all-electronic, fully open exchange. TAL provides engineered direct-access solutions for money managers, asset managers, hedge funds and mutual funds worldwide. During the period of our data storing, TAL was owned by Lehman Brothers.

In 2007 TAL reached the capacity to handle over 1 million ticks per second, from over 2,6 million of traded instruments on the same ticker plant. TAL was the first company to reach that limit that was much enhanced in 2008.

Figure 1- Hermes architecture and topology



Source: Townsend Analytics, Ltd. (TAL), 2007.

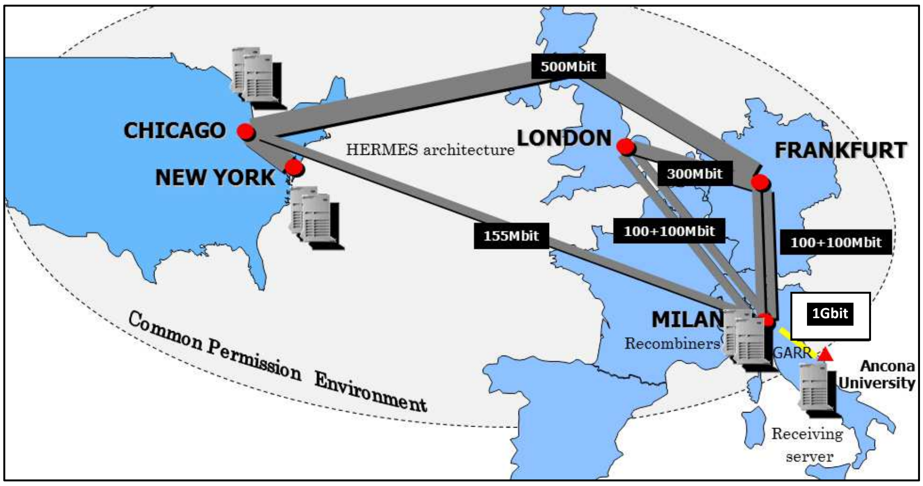
Figure 1 describes the “ticker plants” model and the sequential treatment of raw data from exchanges to clients. Data source is a direct market access to several exchanges, through dedicated private lines covering a range of financial products (equities, futures options, etc..).

Data normalization is processed by *Feed Handlers* and *Headends*. A *Feed Handler* accept data feed from an Exchange, create a symbology, convert data to TAL4 format, and transfer data to a *Headend*. A *Headend* adds symbols, stores symbol state, inserts value-added calculations, provides for data organization (relational model, splitting by symbol), and finally it multicasts data to a *Cacheserver*, starting the process of data distribution. A Cashserver caches data and send data to a Recombiner. A Recombiner routes user queries, enforces entitlements, maintains symbol mapping and finally compress data and send it to clients.

Connections among entities/nodes drawn in Figure 1 are supported by a Multiprotocol Label Switching (MPLS) system that is a mechanism, in high-performance telecommunications networks, that directs data from one network node to the next, based on short path labels. All these connections result into a Wide Area Network (WAN) of TAL propriety.

An idea of the WAN which is beyond the TAL streaming of data, is drawn in Figure 2 which describes Realtick architecture, with US and Europe. TAL Distributed system is based on multiple nodes with the same function in distributed locations (Chicago, New York, London, Frankfurt and Milan). Large attention is given to redundancy, in terms of location (intra-site and inter-site), network (physical switch redundancy), hardware (redundant servers), software (rollover capabilities).

Figure 2- Realtick architecture and network interconnections



Source: Revised from Investnet, 2008.

From Figure 2 it is manifest the network of connections beyond our real-time streaming. The receiving dedicated server based in the Ancona University was connected with a dedicated server (formerly called *Tuber*) connected to the recombiner server network based in Milan, at Investnet. Connection between Ancona University and Investnet's server in Milan was supported by GARR, the Italian Research & Education Network (NREN), that plans and operates the national high-speed telecommunication network for University and Scientific Research. Conversely, Investnet server was connected to the TAL Wide Area Network that finally ensure the direct access into exchanges.

Appendix 2: List of Stocks included in the analysis

Name	ISIN	Market	Name	ISIN	Market
ALLIANZ SE VNA O.N.	DE0008404005	XETRA	APPLE INC	US0378331005	NASDAQ
BASF SE O.N.	DE0005151005	XETRA	ADOBE SYS INC	US00724F1012	NASDAQ
BAYER AG O.N.	DE0005752000	XETRA	APPLIED MATLS INC	US0382221051	NASDAQ
BEIERSDORF AKT	DE0005200000	XETRA	AMGEN INC	US0311621009	NASDAQ
BAY.MOTOREN WERKE AG ST	DE0005190003	XETRA	AMAZON COM INC	US0231351067	NASDAQ
COMMERZBANK AG O.N.	DE0008032004	XETRA	BIOGEN IDEC INC	US09062X1037	NASDAQ
CONTINENTAL AG	DE0005439004	XETRA	CELGENE CORP	US1510201049	NASDAQ
DAIMLER AG NA O.N.	DE0007100000	XETRA	COSTCO WHSL CORP NEW	US22160K1051	NASDAQ
DEUTSCHE BOERSE NA O.N.	DE0005810055	XETRA	CISCO SYS INC	US17275R1023	NASDAQ
DEUTSCHE BANK AG NA O.N.	DE0005140008	XETRA	DELL INC	US24702R1014	NASDAQ
DEUTSCHE POST AG NA O.N.	DE0005552004	XETRA	DIRECTV GROUP INC	US25459L1061	NASDAQ
DT.TELEKOM AG NA	DE0005557508	XETRA	EBAY INC	US2786421030	NASDAQ
HEIDELBERGCEMENT AG	DE0006047004	XETRA	ELECTRONIC ARTS INC	US2855121099	NASDAQ
LINDE AG O.N.	DE0006483001	XETRA	EXPRESS SCRIPTS INC	US3021821000	NASDAQ
MAN SE ST	DE0005937007	XETRA	FIRST SOLAR INC	US3364331070	NASDAQ
METRO AG ST O.N.	DE0007257503	XETRA	GENZYME CORP	US3729171047	NASDAQ
MUENCH.RUECKVERS.VNA O.N.	DE0008430026	XETRA	GILEAD SCIENCES INC	US3755581036	NASDAQ
RWE AG ST O.N.	DE0007037129	XETRA	INTEL CORP	US4581401001	NASDAQ
SAP AG O.N.	DE0007164600	XETRA	JUNIPER NETWORKS INC	US48203R1041	NASDAQ
K + S AKT	DE0007162000	XETRA	MICROSOFT CORP	US5949181045	NASDAQ
SIEMENS AG NA	DE0007236101	XETRA	NORTHERN TR CORP	US6658591044	NASDAQ
THYSSENKRUPP AG O.N.	DE0007500001	XETRA	ORACLE CORP	US68389X1054	NASDAQ
VOLKSWAGEN AG ST O.N.	DE0007664005	XETRA	PAYCHEX INC	US7043261079	NASDAQ
ANGLO AMERICAN	GB00B1XZS820	LSE	PACCAR INC	US6937181088	NASDAQ
AVIVA	GB0002162385	LSE	QUALCOMM INC	US7475251036	NASDAQ
ASTRAZENECA	GB0009895292	LSE	SCHWAB CHARLES CORP NEW	US8085131055	NASDAQ
BAE SYSTEM	GB0002634946	LSE	STAPLES INC	US8550301027	NASDAQ
BARCLAYS	GB0031348658	LSE	SYMANTEC CORP	US8715031089	NASDAQ
BRITISH AMERICAN TOBACCO	GB0002875804	LSE	PRICE T ROWE GROUP INC	US74144T1088	NASDAQ
BG GRP	GB0008762899	LSE	YAHOO INC	US9843321061	NASDAQ
BHP BILLITON	GB0000566504	LSE	ABBOTT LABS	US0028241000	NYSE
BP	GB0007980591	LSE	AMERICAN INTL GROUP INC	US0268741073	NYSE
BT GROUP	GB0030913577	LSE	BOEING CO	US0970231058	NYSE
CENTRICA	GB00B033F229	LSE	BANK OF AMERICA CORPORATION	US0605051046	NYSE
DIAGEO	GB0002374006	LSE	CITIGROUP INC	US1729671016	NYSE
EURASIAN	GB00B29BCK10	LSE	CONOCOPHILLIPS	US20825C1045	NYSE
GLAXOSMITHKLINE	GB0009252882	LSE	CHEVRON CORP NEW	US1667641005	NYSE
HSBC HLDGS.UK	GB0005405286	LSE	DISNEY WALT CO COM DISNEY	US2546871060	NYSE
IMP.TOBACCO GRP	GB0004544929	LSE	GEN ELECTRIC CO	US3696041033	NYSE
LLOYDS TSB GRP.	GB0008706128	LSE	GOLDMAN SACHS GROUP INC	US38141G1040	NYSE
NATIONAL GRID	GB00B08SNH34	LSE	HEWLETT PACKARD CO	US4282361033	NYSE
PRUDENTIAL	GB0007099541	LSE	INTERNATIONAL BUSINESS MACHS	US4592001014	NYSE
RECKITT BEN. GP	GB00B24CGK77	LSE	JOHNSON & JOHNSON	US4781601046	NYSE
ROYAL BANK SCOT	GB0007547838	LSE	JP MORGAN CHASE & CO	US46625H1005	NYSE
RIO TINTO	GB0007188757	LSE	COCA COLA CO	US1912161007	NYSE
SABMILLER	GB0004835483	LSE	MCDONALDS CORP	US5801351017	NYSE
SCOTTISH & SOUTHERN ENERGY	GB0007908733	LSE	MONSANTO CO NEW	US61166W1018	NYSE
STAND.CHART.	GB0004082847	LSE	MERCK & CO INC	US5893311077	NYSE
TESCO	GB0008847096	LSE	OCCIDENTAL PETE CORP DEL	US6745991058	NYSE
UNILEVER	GB00B10RZP78	LSE	PEPSICO INC	US7134481081	NYSE
VODAFONE GRP.	GB00B16GWD56	LSE	PFIZER INC	US7170811035	NYSE
XSTRATA	GB0031411001	LSE	PROCTER & GAMBLE CO	US7427181091	NYSE
ACEA	IT0001207098	BIt	PHILIP MORRIS INTL INC	US7181721090	NYSE
AUTOGRILL	IT0001137345	BIt	AT&T INC	US00206R1023	NYSE
ALLEANZA ASS .	IT0000078193	BIt	UNITED TECHNOLOGIES CORP	US9130171096	NYSE
BCA MPS	IT0001334587	BIt	VERIZON COMMUNICATIONS INC	US92343V1044	NYSE
BUZZI UNICEM	IT0001347308	BIt	WELLS FARGO & CO NEW	US9497461015	NYSE
BCA CARIGE .	IT0003211601	BIt	WAL MART STORES INC	US9311421039	NYSE
EDISON .	IT0003152417	BIt	EXXON MOBIL CORP	US30231G1022	NYSE
ENEL .	IT0003128367	BIt	ACCOR SA	FR0000120404	PARIS SE

Name	ISIN	Market	Name	ISIN	Market
FIAT .	IT0001976403	BIt	CREDIT AGRICOLE	FR0000045072	PARIS SE
FINMECCANICA	IT0003856405	BIt	AIR LIQUIDE	FR0000120073	PARIS SE
FONDIARIA-SAI	IT0001463071	BIt	ALSTOM	FR0010220475	PARIS SE
GENERALI ASS	IT0000062072	BIt	DANONE	FR0000120644	PARIS SE
GEOX	IT0003697080	BIt	BNP PARIBAS	FR0000131104	PARIS SE
HERA	IT0001250932	BIt	CARREFOUR	FR0000120172	PARIS SE
ITALCEMENTI	IT0001465159	BIt	CHRISTIAN DIOR	FR0000130403	PARIS SE
LUXOTTICA GROUP	IT0001479374	BIt	AXA	FR0000120628	PARIS SE
MEDIOBANCA .	IT0000062957	BIt	VINCI (EX.SGE)	FR0000125486	PARIS SE
MEDIOLANUM .	IT0001279501	BIt	EDF	FR0010242511	PARIS SE
MEDIASET S.P.A	IT0001063210	BIt	BOUYGUES	FR0000120503	PARIS SE
PIRELLI E C	IT0000072725	BIt	ERAMET	FR0000131757	PARIS SE
PARMALAT	IT0003826473	BIt	FRANCE TELECOM	FR0000133308	PARIS SE
BCA POP MILANO	IT0000064482	BIt	SOCIETE GENERALE	FR0000130809	PARIS SE
SAIPEM	IT0000068525	BIt	NATIXIS	FR0000120685	PARIS SE
SNAM RETE GAS	IT0003153415	BIt	LAFARGE	FR0000120537	PARIS SE
TELECOM ITALIA	IT0003497168	BIt	LVMH	FR0000121014	PARIS SE
TERNA	IT0003242622	BIt	L'OREAL	FR0000120321	PARIS SE
UNIPOL .	IT0001074571	BIt	PERNOD RICARD	FR0000120693	PARIS SE
			RENAULT	FR0000131906	PARIS SE
			SANOFI-AVENTIS	FR0000120578	PARIS SE
			SAINT GOBAIN	FR0000125007	PARIS SE
			SCHNEIDER ELECTRIC	FR0000121972	PARIS SE
			UNIBAIL-RODAMCO	FR0000124711	PARIS SE
			VEOLIA ENVIRON.	FR0000124141	PARIS SE
			VIVENDI	FR0000127771	PARIS SE

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