"נזילות סוחרים" כמדד נזילות חדש בשווקים פיננסיים

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בעקבות המשבר הפיננסי שהחל ב-2008, גבר העניין בסוגיית הנזילות בשווקים פיננסיים בקרב המערכת הפיננסית העולמית. בתקופה שלאחר המשבר, ובעקבות השלכותיו על הכלכלה העולמית, תיאוריות כלכליות מובילות החלו להיבחן מחדש, במטרה למתן משברים כלכליים עתידיים. בתור כך, עבודה זו מציגה גישה חדשה לנושא נזילות בשווקים פיננסיים. מקובל לקשר את נזילות השוק למשתנים ניצפים המקושרים פעילות המסחר, למשל נפח המסחר או השווי הכפסי של נפח המסחר. כאן אנו מציגים מדדים חדשים של נזילות, מבוססים על מידע חדש של השוק. על ידי שימוש במידע מצטבר על חשבונות יחודיים של סוחרים, אנו מציגים מדדי נזילות חדשים על בסיס שינויים בהרכב המשתתפים בשוק (מוכרים, קונים, או שניהם). בנוסף להצגת המדדים החדשים, אנו בוחנים בצורה כמותית כיצד הם קשורים לשינויי מחיר בנייר הערך, בהשוואה למדדי נזילות מקובלים. התוצאות שלנו מראות שלפער בין מספר הקונים למספר המוכרים יש יכולת חיזוי משופרת, על פני מדדים אחרים, בניבוי שינויים במחיר של נייר הערך. התוצאות המוצגות מספקות מדדים חדשים לניטור וניהול נזילות השוק ומאירות באור חדש את המנגנונים המנהלים את הדינמיקה של השווקים הפיננסיים.

Trader Liquidity as a new liquidity measure for financial markets

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Abstract

The world's economies and financial systems have become highly concerned with the issue of market liquidity, following the onset of the 2008 financial crisis. In the aftermath of this crisis, and as a result of its fallouts, key economic theories and concepts are being reexamined, in aim to mitigate future economic shocks and crises. As such the purpose of this work is to present a new approach to market liquidity. Market liquidity is most commonly related to observables relating to transactions - volume, volume in money worth - or information on the order book - book depth, book gaps. Here we present new measures of liquidity, based on novel market information. Using aggregated information of coded unique trader accounts, we present new liquidity measures based on changes in the makeup of market participants (be it on the selling side, buying side, or both). In addition to presenting these new measures, we quantitatively explore how they relate to price changes of the given asset. Our results show that the difference between number of sellers and buyers can have a predictive power over the underlying asset price changes, as well as sme of the there newly introduced measures. The results presented here provide new measures to monitor and manage market liquidity, and shed new light on the underlying mechanisms governing the dynamics of financial markets.

INTRODCUTION

The worldwide financial crisis of 2008 was triggered by a liquidity shortfall in the United States banking system [1, 2]. It has resulted in the collapse of large financial institutions, the bailout of banks by national governments, and downturns in stock markets around the world. In the aftermath of this crisis, strong criticism has been articulated on credit rating agencies, central banks, and regulators for failing to characterize and properly regulate the financial markets 0f the 21^{st} century.

One of the key factors of this financial crisis was the lack of liquidity. Liquidity is commonly associated with the volume of trade [3]. After price, volume is one of the most commonly quoted data points related to the stock market. Reflecting the overall activity in a stock or market, volume is the business of the market itself: the buying and selling of shares. As such, volume is an important indicator for traders in analyzing market activity and planning strategy. Volume is a measure of market liquidity based on the number of shares that are traded over a given period. However, the liquidity of an asset reflects the ease of converting it into cash. Thus, high volume does not necessarily translate into high liquidity. Much work has been devoted to the study of market liquidity, and to identifying the means to quantify and manage market liquidity [4–7].

For example, consider the two following scenarios. In the first, there are 200 traders 100 sellers and 100 buyers, so there are exactly 100 transactions. In each transaction 10000 shares are exchanged, which makes the total volume 1000000 shares. In the second scenario, there are only two traders one buyer and one seller. In their transaction, again, 1000000 shares are exchanged. In both cases the volume is the same, however clearly the liquidity in the first scenario is much higher. This example shows that the number of shares, or their cash equivalent, can be misleading regarding the true liquidity of the asset.

Thus, we propose to define a new measure of liquidity, not based on the number of shares or the money equivalent in number of shares. We propose a measure, in which we study the number of different traders that are active on a given asset, in a given time horizon. This trader liquidity will provide a quantitative measure to the given popularity of the asset at a given time and as a result, a better liquidity measure.

The main objective of this research is to define a new quantitative measure of liquidity. We will use transaction data with a code for the given account performing the transaction, for different assets traded in the Tel-Aviv market. We will quantify the number of different accounts active on the asset (either buying or selling), for a given time horizon. We will investigate the information contained in the trader liquidity parameter.

DATA

Recent technological advances have made available extremely large data sources, which can be used in the study of the dynamics and behavior of financial markets [8–17]. Financial time series data in the resolution of the individual trader (coded identity) has only recently become available [13, 18]. Thus, the proposed liquidity measure is a new measure, which was unfeasible in the past. As such, the proposed research is truly innovative and capable of extracting new information on the market and its dynamics. In this work we investigate a special database on all assets traded in the Tel-Aviv market. The data has mainly been collected from the TASE (Tel-Aviv Stock Exchange). This database is comprehensive and of high quality. It includes, amongst many others, all orders, cancellations and trades going on at the exchange (the only exchange in Israel); nevertheless, its' main advantage is that every order/cancellation has a unique encrypted signature of the trading account sending the order/cancellation. The data has been carefully collected by the Economic Research Department of the ISA.

For each transaction, the dataset includes all standard financial variables (time, price, volume, number of shares), and additionally a coded ID of the account that participated in the selling side, and the buying side. Each individual ID can participate a number of times in a given time horizon. Thus, we can study the aggregated number of unique individual ID's active in a given time horizon, on the buying side, selling side, or total number of unique traders participating in the given time horizon. Finally, we investigate passive accounts, which are accounts that played the role of a "maker" in some trade during the interval. The role of maker for a trade is that side of the trade which sends its buy/sell order prior to the order of the other side of the trade. This side "created" the liquidity, while the ACTIVE side (or the "taker") "reduced" the liquidity. In this study we focus on a time horizon Δt of 1 trading hour, however the analysis presented here can be applied to any chosen time horizon. The total period investigated spans from February 2008 to October 2012. The full dataset includes all securities traded at the TASE (excluding plain vanilla derivatives:

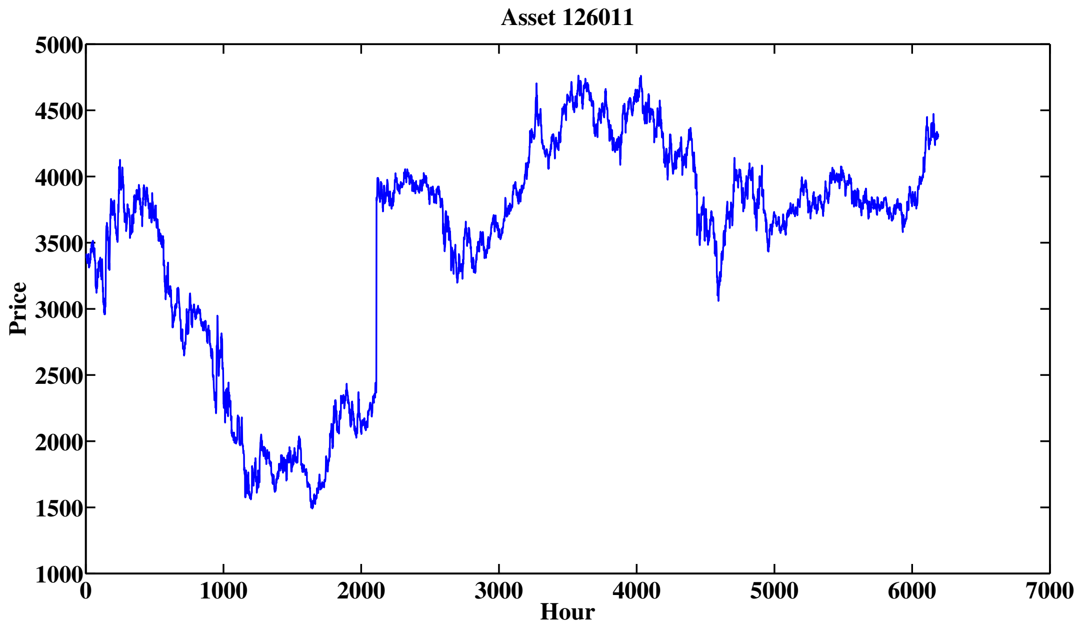

FIG. 1: Price time series of asset 126011, on a hourly basis, from Februrary 2008 to October 2012.

PUTs/CALLs/FUTUREs), which in total is roughly 12 million rows.We emphasize that we do not study individual account activity, rather aggregated activity of different traders over a given time window.

Here we focus only on stocks that belonged to the Tel-Aviv 25 market index (TA25) during the investigated time period. Due to index changes, in total there were 39 such assets (in the future we will expand this work to include all assets traded in the TA market). To study the affect of the different liquidity measures on the asset price, we transform the price into the logarithmic return [19]

$$r_i(t) = log(P_i(t)) - log(P_i(t-1)), \tag{1}$$

where $P_i(t)$ is the price of asset i at time t, and the time t is measured here in transaction time (i.e. each time record t corresponds to a time stamp of a given transaction). In Figure 1 we present an example of the price versus return of a given asset.

TRADER LIQUIDITY MEASURES

In this section we introduce two new liquidity measures, based on the number of unique traders active in time window Δt. The first is calculated by investigating the changes in number of unique traders, and the second is is calculated by studying the number or value of the transactions made by the unique traders in the given time window.

Unique trader liquidity

Here we introduce a new liquidity measure, based on the number of active unique traders. For a given time horizon Δt, we calculate the aggregated number of unique seller ID's ($n_{seller,\Delta t}$), aggregated number f unique buyers ($n_{buyer,\Delta t}$), and aggregated number of unique participants ($N_{\Delta t}$), which is given as

$$N_{\Delta t} = n_{seller,\Delta t} \bigcup n_{buyer,\Delta t} \tag{2}$$

where $\bigcup$ is the union of the aggregated unique sellers and aggregated unique buyers, which results in the aggregated number of unique participants. Using these aggregated observables, we calculate the Trader Liquidity Index (TLI) κ:

$$\kappa = \frac{n_{seller,\Delta t} - n_{buyer,\Delta t}}{N_{\Delta t}}. \tag{3}$$

κ can be calculated for either individual assets, a portfolio of assets, all assets making up a market index, or the entire market. Negative values of κ represent market states in which

Trader Herfindahl Index

The Herfindahl index (also known as HerfindahlHirschman Index, or HHI) [20] is a measure of the size of firms in relation to the industry and an indicator of the amount of competition among them. Named after economists Orris C. Herfindahl and Albert O. Hirschman, it is an economic concept widely applied in competition law, antitrust and also technology management. It is defined as the sum of the squares of the market shares of the 50 largest firms (or summed over all the firms if there are fewer than 50) within the industry, where the market shares are expressed as fractions. The result is proportional to the average market share, weighted by market share. As such, it can range from 0 to 1.0. Increases in the Herfindahl index generally indicate a decrease in competition and an increase of market power, whereas decreases indicate the opposite. The index is defined as

$$H = \sum_{i=1}^{N} s_i^2. \tag{4}$$

where s_i is the market share of firm i in the market, and N is the number of firms. Thus, in a market with two firms that each have 50 percent market share, the Herfindahl index equals 0.5. The Herfindahl Index (H) ranges from 1/N to one, where N is the number of firms in the market. The level of market concentration can be derived from the values of the Herfindahl index, where:

- A HHI index below 0.01 indicates a highly competitive index.
- A HHI index below 0.15 indicates an unconcentrated index.
- A HHI index between 0.15 to 0.25 indicates moderate concentration.
- A HHI index above 0.25 indicates high concentration.

Finally, it is possible to consider a normalized version of the Herfindahl index. Whereas the Herfindahl index ranges from 1/N to one, the normalized Herfindahl index ranges from 0 to 1. It is computed as:

$$H^* = \frac{(H - {}^1/_N)}{1 - {}^1/_N} \tag{5}$$

In this work, we consider two types of Herfindahl like measures, which are calculated for the unique accounts:

1 Unweighted Herfindahl (H_1): For the given time horizon Δt, for each unique account we calculate how many transactions it was active on, relative to the total number of transactions in the given time horizon, and take the square of this ratio. Thus, in the case studied here of $\Delta t = 1hour$, we calculate the average number of relative transactions of each unique account. This measure is calculated separately for the sellers, buyers, participants, and passive traders.

2 Weighted herfindahl (H_2): For the given time horizon Δt, for each unique account we calculate how many transactions it was active on, weight each transaction by its value (price multiplied by number of shares), divide it by the total value of transactions in the given time horizon, and take the square of the ratio. We do this for each unique accounts for all of its transactions, and average over all accounts. This is calculated for sellers, buyers, participants, and passive traders.

LIQUIDITY MEASURES

In this section we discuss alternative liquidity measures, which are not calculated using the information about unique trader accounts. Here we focus on three such liquidity measures - Kyle's λ, Effective Spread, and Cost of Round Trip (CRT).

Kyle λ

Kyle's Lambda, defined as the slope from regressing absolute returns to volume over some time window (often as short as 15 minutes). For very short periods, this reduces to simply

$$\lambda = \frac{\Delta Price_t}{Volume_t}. \tag{6}$$

Volume is typically measured as turn-over or the value of shares traded, not the number. Under this measure, a highly liquid stock is one that experiences a small price change for a given level of trading volume. Here we focus on two versions of the Kyle λ:

1 $Kyle_1$ is a measure of market depth (liquidity) in which we take for each trade its price move (in %) (in absolute value) and divide it by the cash value of the trade. The higher the number, the easier it is to move the price, and the less liquid the security. We calculate the $Kyle_1$ for each trade in the interval and take the mean.

2 $Kyle_2$ is similar in concept to $Kyle_1$, so we measure the price shift (P) of the trade and its cash value (V). However, instead of simply dividing the two quantities, we first normalize each of them with respect to all measurements of price shift and cash value respectively. Finally we take the mean of this quantity over all trades in the interval. The Normalizing is a process in which we first remove outliers (those samples

with $|Zscore| > 1.96$ and below the 2.5^{th} or above the 97.5^{th} percentile), then find the maximum and minimum value of the non-outlier samples. Finally we take each sample S and calculate $(S-min)/(max-min)$ to put the population in the [0,1] interval and finally we assign values of 0 to the lower outliers and 1 to the high outlier, respectively. This process standardizes the samples to the [0,1] interval, while conserving the shape of the distribution and at the same time being robust to outliers.

Effective spread

Here we introduce a liquidity measure which is based on the Order Book. Using the information on different levels of the book, we can calculate at each instant a liquidity measure which will be based on the spread of the different levels. As such, here we perform the calculations on a 5-minute interval, and then calculate the average over all intervals in the given hour. We define two Effective spread measures:

1 Effective Spread 1 (ES_1), is the % loss for buying 1 share and immidiately selling it, defined as

$$ES_1 = 100 \cdot \frac{(BestAsk - BestBid)}{BestAsk}. \tag{7}$$

2 Effective Spread 2 (ES_2), is the spread divided by the mid price, defined as

$$ES_2 = 100 \cdot \frac{(BestAsk - BestBid)}{0.5 \cdot (BestAsk + BestBid)} \tag{8}$$

Cost of Round Trip (CRT)

CRT is short for (Cost of Round Trip), and is well known as a liquidity measure. For a given cash value V, we ask the question, if we buy shares from the order book with V and then immediately sell all those shares, what % of V will we loose? So V is in a sense the depth of the book that we are digging in to measure the spread at that level of depth. Here we investigate three different CRT measures:

1 CRT_1 - we calculate CRT with V being 5% of the daily turnover in the given security.

2 CRT_2 - we calculate CRT with V being 5% of the daily mean cash value of all trades at the exchange.

3 CRT_3 - we calculate CRT with V being the cost of clearing one side of the book (buy or sell-depending on which side has less shares in it).

RESULTS

In the time of the writing of this report, we had not finalized the calculations for the Effective Spread and CRT liquidity measures. These calculations are on-going, and once finalized will be added to the analysis presented below. Thus, here we focus on the κ index, the different Herfindahl indices, and the Kyle λ indexes.

Analysis of liquidity measures

For each of the 39 assets that belonged to the TA25 in the investigated time period, we calculate the different liquidity measures. First, we calculate the κ liquidity index (see for example Figure 2), for the different assets. Positive values of κ reflect a state in which there are more sellers than buyers, and negative values reflect a state in which there are more buyers than sellers. In Figure 3 we present the histogram of values of the κ index for all 39 assets investigated.

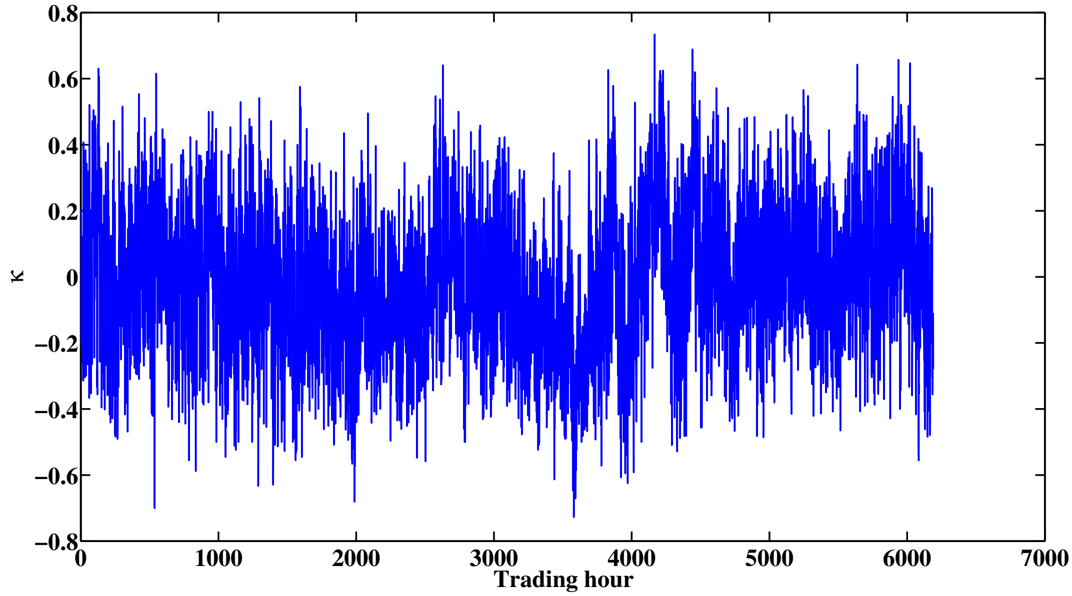

FIG. 2: Example of the κ index as a function of trading hour, for asset 126011. κ is calculated as the difference between number of unique sellers and unique buyers divided by number of unique participants.

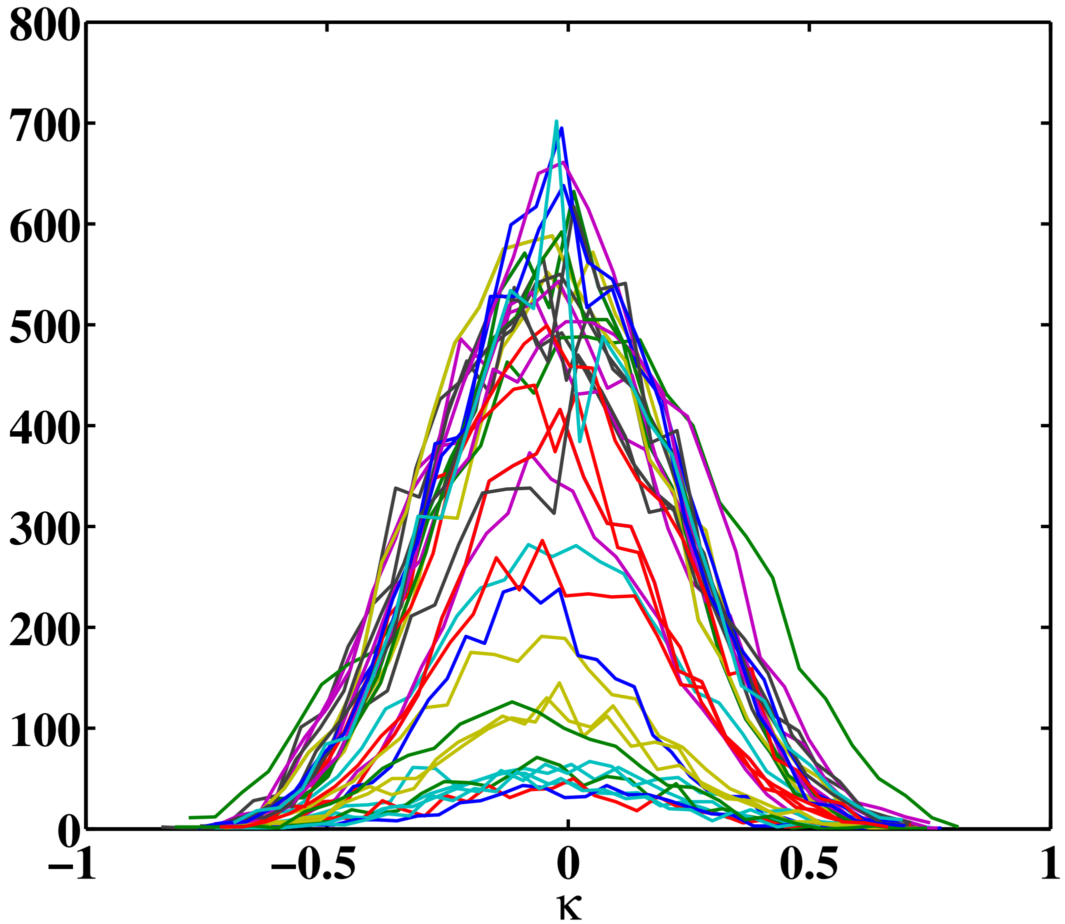

FIG. 3: Histogram of the values of κ for all 39 assets investigated.

We study the time behavior of the κ index, using the well known Detrended Fluctuation Analysis (DFA) [21, 22]. For the example of the asset 126011, we find that the DFA results in $\alpha = 0.89$. A value of α greater than 0.5 and less or equal to 1 indicates persistent long-range power-law correlations, such that a large (compared to the average) value of κ is more likely to be followed by a large value, and vice versa. For all 39 assets, we find $\alpha = 0.7734 \pm 0.0873$.

Next, we calculate the unweighted (H_1) and weighted (H_2) Herfindahl index for the sellers, buyers, and participants separately. Furthermore, we calculate both measure for the passive traders. Finally, we calculate the two Kyle λ indexes, which serve as an alternative liquidity measure that is based on the transaction prices. In this work we focus on the Herfindahl measures for the participants (active and passive), the two Kyle measures (total of six additional liquidity measures). In Figure 4 we present an example of the six measures, for a given asset, and in Figure 5 the histogram of all values for the 39 investigated assets, for all six liquidity measures..

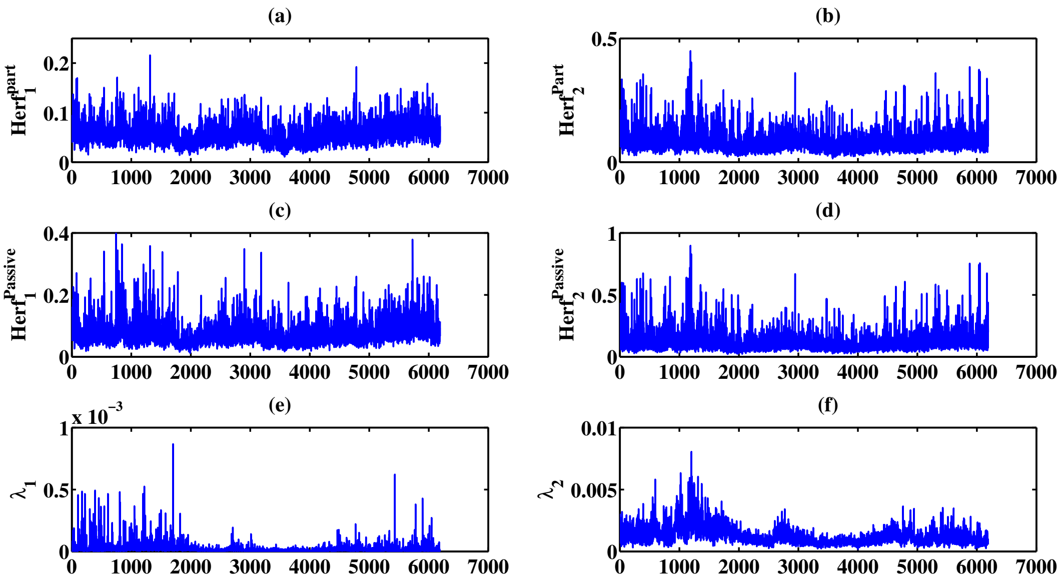

FIG. 4: Different liquidity measures for asset 126011, as an example: (a) Unweighted Herfindahl for participants, $Herf_1^{Part}$, (b) Weighted Herfindahl for participants, $Herf_2^{Part}$, (c) Unweighted Herfindahl for passive traders, $Herf_1^{Passive}$, (d) Weighted Herfindahl for passive traders, $Herf_2^{Passive}$, (e) Kyle Lambda, λ_1, and (f) normalized Kyle Lambda, λ_2.

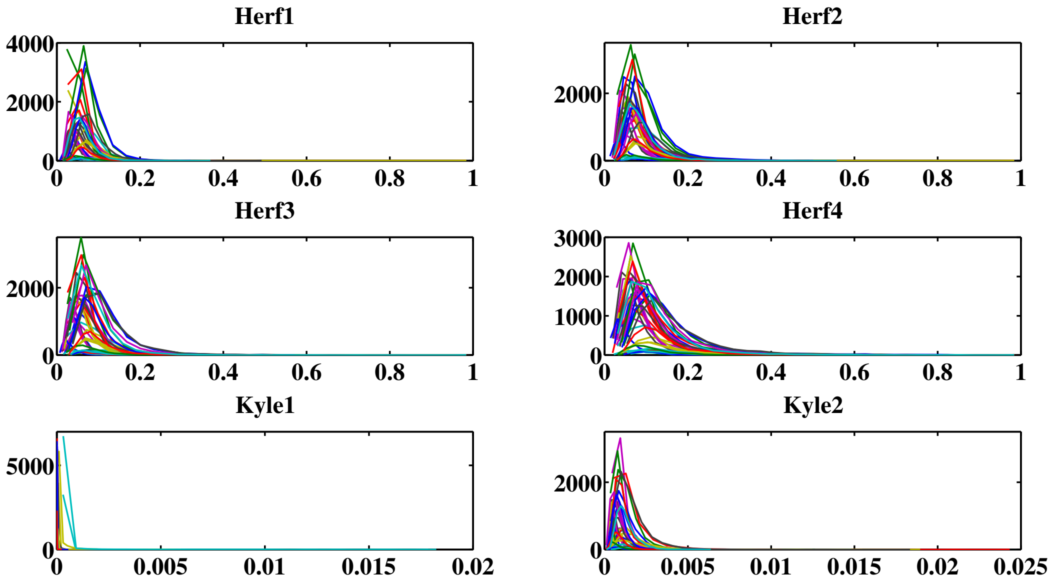

FIG. 5: Histogram of the values of all six liquidity measures, for the 39 assets investigated: unweighted participant Herfindahl (Herf1), weighted participant Herfinfdahl (Herf2), unweighted passive traders Herfindahl (Herf3), weighted passive traders Herfindahl (Herf4), Kyle lambda (Kyle1), and normalized Kyle Lambda (Kyle2).

Similarity between liquidity measures and asset return

The aim of this study is to investigate whether the new proposed liquidity measures can provide information on asset price changes. In this section we study the correlation between the seven liquidity measures discussed above, and the asset return. To this end, we make use of the Pearson correlation coefficient [23],

$$\rho(Liq_i, R) = \frac{1}{N} \sum_{t=1}^{N} \frac{(Liq_{i,t} - \mu_{Liq_i}) \cdot (R_t - \mu_R)}{\sigma_{Liq_i} \cdot \sigma_R}. \tag{9}$$

where Liq_i is one of the liquidity measures, R is the asset return, t is each time record (in this case one hour) and N total number of time records, μ is the average and σ standard deviation.

In Figure 6 we present the correlation between the seven liquidity measures, and the asset return, for each of the 39 assets. We observe higher values of correlation between the κ liquidity measure and asset return, across all 39 assets. Furthermore, we find only positive correlations for the case of κ, whereas for the other liquidity measures, some assets also exhibit negative correlation with the return.

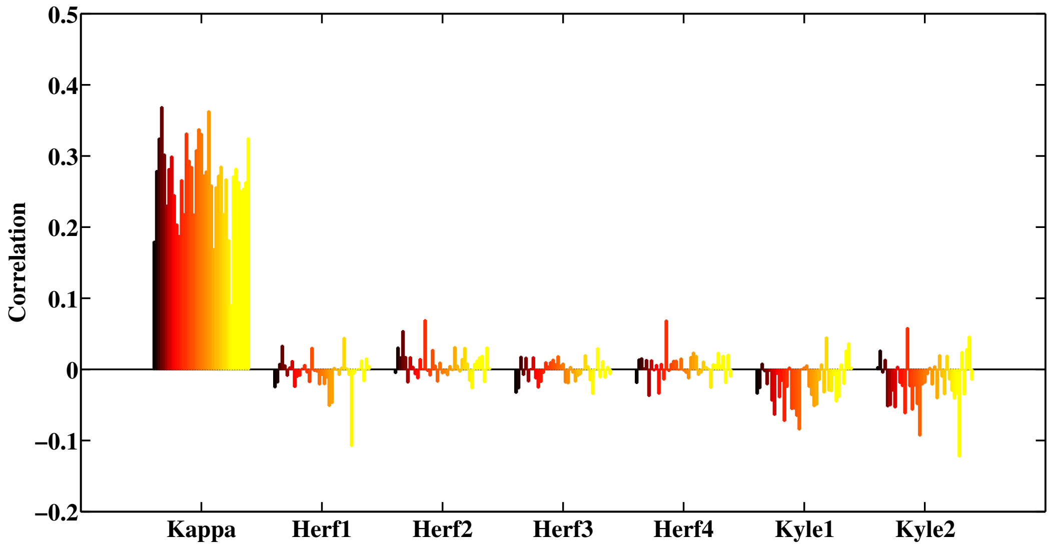

FIG. 6: Correlation of liquidity measures with stock return. For all stocks belonging to the TA25 index, in the investigated period (39 in total), we calculate the correlation between the different liquidity measures and the stock return. The liquidity measures considered are: the difference between number of unique sellers and unique buyers divided by number of unique participants (Kappa), unweighted participant Hefindahl (Herf1), weighted participant herfindahl (Herf2), passive trader Herfindahl 1 (Herf3), volume weighted passive trader Herfindahl (Herf4), Kyle Lambda (Kyle1), and normalized Kyle Lambda (Kyle2). The different stocks are marked by different colors.

Causal relationships between liquidity measures and asset return

Finally, to further validate our results, we make use of the Granger Causality Analysis (GCA) to analyze the extent to which the average component correlation is useful in predicting the index return, or vice versa. Granger causality uses temporal precedence to identify the direction of causality from information in the data [22, 24–26]. Thus, given the two time series R and a liquidity variable Liq_i, we can independently identify both influence from R to Liq_i, and influence in the reverse direction with suitable models. A measure of linear dependence $F_{Liq_i,R}$, between Liq_i and R, which implements Granger causality in terms of vector autoregressive models, has been proposed by Geweke [27]. $F_{Liq_i,R}$ is the sum of three components

$$F_{Liq_i,R} = F_{Liq_i \to R} + F_{R \to Liq_i} + F_{R \cdot Liq_i}. \tag{10}$$

$F_{R \cdot Liq_i}$ is a measure of the total linear dependence between the series R and Liq_i. If none of the value at a given instant of one can be explained by a linear model containing all the values (past, present, and future) of the other, $F_{R \cdot Liq_i}$ will evaluate to zero. This term contains no directional information, and represents residual correlations in the data that cannot be assigned to causally directed influence based on the information in the data. $F_{Liq_i \to R}$ is a measure of linear directed influence from Liq_i to R. If past values of Liq_i improve the prediction of the current value of R, then $F_{Liq_i \to \Sigma R} > 0$. Here we follow the work of Billio *et al.* [28], and assign a binary value of 1 for significant Granger causality above a significant value of $\alpha = 1\%$, or 0 otherwise.

For each of the 39 investigated assets, we perform the GCA of each of the seven liquidity measures (κ, four Herfindahl indexes, and two Kyle λ indexes) versus the asset return, using the first order GCA (which uses a lag of one time record, one hour in this case). We find that for 12 of the 39 assets (31%), there is a significant Granger causality relationship between one of the liquidity indexes and the asset return. Out of these, in 8 of the 12 cases (75%) we find that the κ liquidity measure has a significant granger causality with the asset return.

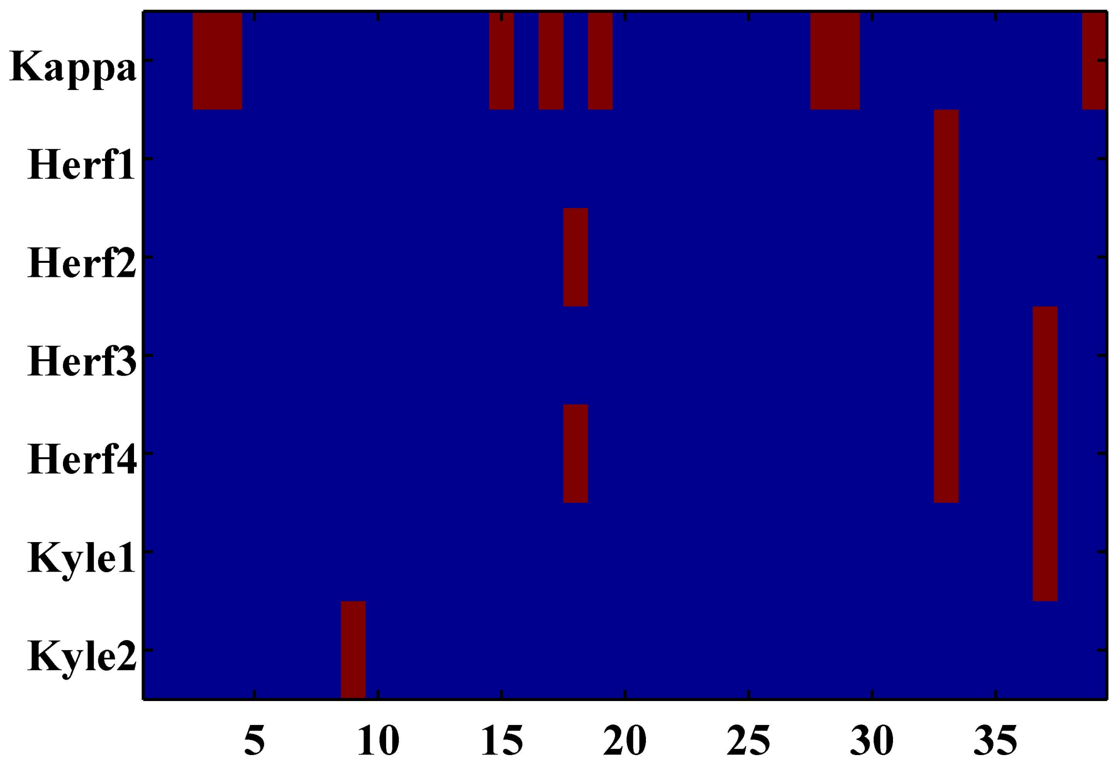

FIG. 7: Granger causality analysis of the seven liquidity measures (κ, four Herfindahl indexes, and two Kyle λ indexes) versus return, for each of the 39 assets. For each asset, if a liquidity measure had a significant granger casualty relation with the return, at the 1% significance level, we use a binary value of 1, and 0 otherwise.

DISCUSSION

In this work, we present new liquidity measures, which are based on novel information on the activity of traders participating in the market. The newly available access to coded identities of the traders provides a unique peephole to the underlying mechanisms governing the dynamics of financial markets. As financial markets are in essence a system in which many agents (traders) interact, studying the fluctuations of trader numbers, and other related quantities, provides valuable information.

Our results show that the relative change in the difference between number of sellers and buyers can provide significant information on the changes in the price of the underlying asset. Here we made use of the Granger Causality analysis, which only provides information on whether one time series predicts a second time series. This does not provide information on how changes in the κ index can be used to predict chafes in the return of the underlying asset, and we will study this in future work.

In conclusion, we propose that these new liquidity measures will be used by policy makers to monitor and manage the behavior of financial markets. Future work will expand on these results to further explore the relationship between the proposed liquidity measures and market movements.

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