Market Efficiency at the Tel-Aviv Stock Exchange

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Abstract

The question of market efficiency is one of the most important, intriguing and debated issues in finance. The efficient market hypothesis states that the current market price of an asset reflects all the available information concerning the asset, and, therefore, this information cannot be used to predict future prices and earn excess returns. However, in order for the price to incorporate new information, some actions must be performed by traders that receive the information. Therefore, some time must elapse until a new equilibrium state is reached. How long does this take? We study the issue of convergence to efficiency at the Tel-Aviv Stock Exchange. We examine various parameters that can be predictive of the returns, including features of the limit order book. Furthermore, we take trading fees into account and conclude that some form of market efficiency holds even at the smallest time horizon.

1 Introduction

1.1 The Efficient Market Hypothesis and the Speed of Convergence to Efficiency

The question of market efficiency is one of the most important, intriguing and debated issues in finance. It has been studied extensively since the notions of weak, semi-strong and strong efficiency were introduced by Fama in 1970 [14]. The weak form of the efficient market hypothesis states that the current price fully reflects all the information that can be learned from past price movements and, therefore, past price movements cannot be used to predict future prices and earn abnormal risk-adjusted returns. The semi-strong form of the hypothesis asserts that the current price reflects all the publicly available information, so that even if we use a model that incorporates all the data about the asset that is publicly available, we will not be able to get excess returns. The strong form of the hypothesis claims that the current price also incorporates the private information regarding the asset.

It is generally agreed that predicting future prices is very hard and market efficiency holds in some form. Nevertheless, some market anomalies have been discovered and extensively studied [6]. These anomalies have disappeared and some reappeared again throughout the years and their nature and persistence is not entirely clear. It has also been shown that some naive traders act in a consistently inefficient manner, so that their actions and effect on the market can be predicted [6].

So, how does the market become efficient? Clearly, if some new information is received, there must exist traders that act upon it and move the price, until a new equilibrium state is reached. Additionally, if some naive traders exhibit an inefficient trading behavior, such as herding, more sophisticated traders should counteract their influence by taking an opposite position and thus eliminating their impact on the market.

How long does it take to eliminate an inefficiency in the market? It has been agreed that daily returns exhibit no autocorrelation. But what if we look at hourly returns, returns per second or per one tick? Are they still independent?

The question of the speed of convergence to efficiency is both of academic and practical importance. Practitioners invest substantial resources in trying to uncover market inefficiencies and profit from them. At what time resolution should they apply their strategies? At what resolution might arbitrage opportunities still exist?

How might we go about proving market efficiency or inefficiency? Proving inefficiency is much easier than proving efficiency: if we find a profitable strategy based on past price movements, this obviously shows that the market is inefficient. But what about the other direction? If we perform some statistical test that shows no correlation, for example, we run linear regression and get zero coefficients, this still does not mean that the market is efficient: there might be some more complex pattern in the data that we missed. This is analogous to questions in cryptography and pseudorandom generators.

Suppose that we have some encryption algorithm and we are trying to see whether it is secure or not. "Secure" means that the encryption is hard to break, i.e. that given the encrypted content it is "hard" to uncover the unencrypted content. If we find a way to uncover the unencrypted content, then we are done: the algorithm is not secure. But what if we don't find such a way? What if we examine a few ways of breaking the code and see that they don't work? This still does not mean that the code is secure, it just means that the simple ways that we tried might not be sufficient in order to break it. There might exist a more powerful adversary (one that has a more sophisticated algorithm, or more computing resources) that will break the code.

A similar question, that is even more related to market efficiency, is that of "breaking" a pseudorandom generator. A pseudorandom generator is an algorithm that generates a number sequence that "looks random". Breaking the generator means finding a pattern in the output, i.e. showing that the output does not look random. But how can we prove that the generator is secure, i.e. that no pattern can be found? What happens is that the generator might look random to adversaries of certain computing power, but more sophisticated adversaries will be able to spot patterns in the output, refuting the pseudorandomness of the generator.

Going back to the question of market efficiency, it might occur that the market looks efficient to traders with certain limited resources, but more powerful traders (in terms of algorithms and computing power) will discover patterns in the data and exploit them. This view of market efficiency was taken by [18]. However, developing more sophisticated strategies can require considerable investment in research and technological infrastructure. The returns earned by these strategies must be viewed in context of this investment.

Therefore, we study market efficiency with respect to simple strategies that use statistical correlations between various market parameters. Furthermore, we take into account the fees that are imposed by the exchange.

We reach the conclusion that some form of efficiency holds even at the smallest time horizon. Despite the fact that return autocorrelations can be observed for up to about thirty minutes, these cannot be exploited by a simple strategy, taking the trading fees into account.

This paper is organized as follows. We present some related work at section 1.2. We discuss the introduction of electronic limit order books and high frequency trading at section 1.3. We describe our work at section 1.4, including our methodology for efficiency testing, our data, initial results and discussion. We pose our research questions and discuss some future work at section 1.5.

1.2 Related Work

Some research has been done previously on the speed of convergence to market efficiency. Epps (1979) studies the differences in the speed of adjustment of stocks within the same industry to news relevant for this industry [12]. He finds that the speed of adjustment varies and, therefore, sometimes one stock movements are predictive of the others. Still, the adjustment usually takes no longer than one hour.

Patell and Wolfson (1984) study the time it takes for the market to incorporate dividend and earnings information [25]. Their conclusion is that it takes between fifteen to ninety minutes.

Chordia, Roll and Subrahmanyam (2005) study the question of market efficiency at small time resolutions, such as five to thirty minutes [6]. Their model divides the traders into two types: liquidity traders and market makers. They look at the imbalance of orders that come from liquidity traders, defined as the amount of buy orders less the amount of sell orders initiated by these traders. Empirically, the order imbalance is found to be autocorrelated, probably because of herding behavior or splitting of large orders or both. However, stock returns are not autocorrelated, considering the same time horizon. Therefore, smart market making activity must be involved in removing the returns autocorrelation. Chordia et al. define a theoretical model of convergence to market efficiency. The model predicts that, even if a persistent imbalance between buy and sell orders from liquidity traders exists, a large enough market making activity will counteract it and remove the returns correlation.

To support their model, Chordia et al. use NYSE data from the years 1996, 1999 and 2002. They find that, even considering a time horizon as short as five minutes, stock returns are uncorrelated, and, therefore, weak market efficiency holds.

They then proceed to consider the stronger notions of efficiency. For each trade they compute whether it was buyer or seller initiated, which allows them to deduce the order imbalance parameter defined above. They find that autocorrelation between the imbalances remains for time horizons as long as five minutes. These imbalances are correlated to returns in the next time period, as detailed next. For large stocks there is significant correlation between order imbalances and returns in 1996 at the five minutes horizon, refuting strong market efficiency. Strong efficiency is the appropriate measure here, since the information on order imbalances was not available to ordinary traders, but only to the stock specialist and perhaps astute floor traders. This correlation, however, declines to marginal significance in 1999 and insignificance in 2002, evidence for faster convergence to market efficiency in the later years. For mid-capitalization stocks order imbalance remains predictive over five minutes in all years and over ten minutes in 1996 and 1999, suggesting slower convergence for these stocks. For smaller stocks the correlation can sometimes be found even at the fifteen minutes horizon for earlier years.

Considering the result for 2002 above, we see that the imbalances are correlated at the five minutes horizon, but there is no correlation between imbalances and returns. Chordia et al. conclude that market makers and sophisticated arbitrageurs act to remove the correlation of imbalances and returns within a few minutes.

1.3 Electronic Limit Order Books

In recent years many major stock markets have become electronic limit order driven, i.e. most of the trading is done via an electronic order book that matches between the potential buyers and sellers. These exchanges manage the trade by keeping an electronic limit order book that contains all the buy and sell orders for each asset. The entire book or part of it is open for traders to view throughout the trading day. Another change in the markets is related to the rise of high frequency trading. More and more high frequency traders enter the markets every year, becoming a dominating force.

Therefore, it is of great interest to study market efficiency and the speed of convergence under these new circumstances. It is plausible to predict that markets become increasingly efficient and prices converge much faster. Furthermore, it is interesting to study semi-strong and strong efficiency in this context. Various characteristics of the order book, such as order balance, bid-ask spread and even identity of traders may contain valuable information that can be used to predict future returns. Some of these parameters are available to all traders and others are hidden.

The limit order book for a specific asset contains all the limit orders available for that asset. Throughout the day traders can submit market or limit orders. A *market order* is an order to buy or sell a certain quantity at the best available price. A market order is executed as soon as any order of the opposite type exists in the book, usually immediately. A *limit order* is an order to buy a certain quantity at some price p or less or to sell a certain quantity at some price p or more. It is executed as soon as the market receives a matching opposite order. Until a matching order is received the limit order waits in the order book. The limit orders are prioritized by price (the better-priced order is executed first). Orders with the same price are prioritized by time of arrival (the book keeps a queue of orders for each price). The *bid-ask spread* is defined as the lowest price for which a sell order exists (best ask price) less the highest price for which a buy order exists (best bid price). The *mid market* price is defined as (best bid price + best ask price)/2.

The order book dynamics is the driving force behind the "short-term" price movements that we observe in the markets. Many models for the order book dynamics and the price formation mechanism have been proposed [1, 4, 8, 9, 10, 11, 22, 23, 28].

1.4 Our Work

We study various forms of market efficiency and the speed of convergence at the Tel-Aviv Stock exchange. We consider diverse parameters that can be correlated to the returns and take trading fees into account.

1.4.1 Efficiency Testing Methodology

We check returns autocorrelation at various time horizons. The detected autocorrelations are always negative, therefore, the simplest trading strategy that could exploit them is the following. Suppose that we observe a negative return r_{t-1} at time $t-1$. Since the correlation is negative, we predict a positive return at time t, therefore, we take a long position on the stock. Similarly, if r_{t-1} is positive, we assume a short position. In any case, we close the position after r_t is observed. In case our strategy works perfectly, we will earn return $|r_t|$. However, we need to pay a trading fee f, so that the actual return will be $|r_t| - f$. To test market efficiency, we compute $E(|r_t|)$ and test whether it is large enough to justify the fee.

1.4.2 The Data

Our data contains all the deals and orders for all stocks traded on TASE for 2010.

The TASE limit order book is empty at the beginning of each trading day. After a short opening stage, when orders start to flow in, the trading begins. The book is cleared by the end of the day.

The TASE order book is anonymous (the identities of the traders are not displayed) and only three levels of the book are publicly available throughout the trading day (three top bid queues and three top ask queues). Since we have historical data, we can reconstruct the entire book and compute various parameters, such as the number of limit vs. market orders at a certain time period.

We compute the returns for two stocks Bank Leumi (LUMI) and Bank Hapoalim (POLI) at different time horizons ranging from one tick to three hours for the year 2010.

We then find the autocorrelation coefficient and p-value. For each time horizon we first compute the time series of the returns for the two stocks $r_{1,1},...,r_{1,t}$ and $r_{2,1},...,r_{2,t}$. We then put together all the pairs $(r_{i,j}, r_{i,j+1})$ for $i = 1, 2$ and compute the correlation coefficient between $r_{i,j}$ and $r_{i,j+1}$. We group the stocks together, since they are very similar, and we get identical results when computing the autocorrelation separately for each stock. The results are summarized in table 1.

We also compute the mean of the absolute value of the returns for these time horizons, $E(|r_{i,j}|)$, as detailed in table 2.

1.4.3 Initial Results

We currently have results for two stocks: Bank Leumi (LUMI) and Bank Hapoalim (POLI). These stocks are among the top five liquid stocks on TASE.

We reach the following conclusions. The stock returns have significant negative autocorrelation at the smaller time horizons (see figure 4). This finding is similar to the results of Chordia et al. At the tick level, the returns have a -0.19 correlation coefficient with a p-value of 0. At the one-second resolution the returns have a -0.27 correlation coefficient with a p-value of 0. When looking at larger resolutions, the correlation gets weaker and weaker until it vanishes at fifteen to thirty minutes (see table 1). This is similar to the findings of Chordia et al.

1.4.4 Discussion

Why do these correlations remain, despite the possible presence of high frequency traders in the market? Can the correlations be exploited to make excess returns?

We test market efficiency using the simple strategy described above. The strategy expected return is $E(|r_{i,j}|)$. We find that at small time horizons this is not large enough to justify the fee. For example, for time resolution of five seconds $E(|r_{i,j}|) = 0.075\%$, therefore, a fee of just 0.075% will make the strategy not profitable. At five minutes $E(|r_{i,j}|) = 0.127\%$, therefore a fee of 0.127% will make the strategy not profitable (see table 2). We can therefore conclude that, considering the trading fees, the market is efficient with respect to this strategy at time horizons of a few minutes.

1.5 Research Questions and Future Work

We intend to continue investigating market efficiency at TASE, first generalizing our results to include more assets. It is interesting to see whether inefficiency remains for less liquid stocks.

1.5.1 Buyer vs. Seller Initiated Trades

Following Chordia et al., we plan to test whether the balance of buyer vs. seller initiated trades is correlated with the returns in the next time period. We would like to find the maximal time resolution for which correlation exists.

1.5.2 Limit Order Book Features

Some of the order book parameters that we wish to consider are the bid-ask spread and the balance of bid vs. ask volumes at the top levels of the book. The bid-ask spread has been shown to be correlated with the *volatility* in the next time period, [16]. (We wish to thank Thierry Foucault for referring us to [16].) We would like to test that claim on our data and examine the possibility of using the predicted volatility to price the *option* on the asset. We also conjecture that large volatilities appear in chunks (see figure 2) and we would like to incorporate this intuition in our models.

1.5.3 Trading Intensity

We also wish to study correlations of the returns with other characteristics of the trading activity. One of these characteristics is trading intensity, i.e. the trading volume per time period. We found a daily seasonality in the trading intensity, with the hour between 10 and 11 a.m. being the most intense. Therefore, it might be interesting to look at the trading intensity normalized by the mean intensity for the time period. The distribution of the normalized trading intensity is right-skewed (see figure 5). We would like to examine this further and see how it is related to the returns and other parameters.

1.5.4 More Sophisticated Models

We have shown that market efficiency holds with respect to simple strategies. Can we say something regarding more sophisticated strategies? A recent line of research focuses on modeling the limit order book as some form of a stochastic process and using these models to predict price movements and various features of the book [1, 4, 8, 9, 10, 11, 22, 23, 28]. We would like to test these models on our data and develop them further.

We consider a Markov-type model of the trading process. We define S_t, the state at time t, as the tuple of the values of the relevant features at time t, i.e. $S_t = (v_1, v_2, ..., v_m)$. We build a Markov model with a memory of k steps, that is, we assume that the state at time t depends upon k previous states, but is independent of the states beforehand, given these k states, namely $P(S_t|S_{t-1}, S_{t-2}, ..., S_{t-k}, ..., S_1) = P(S_t|S_{t-1}, S_{t-2}, ..., S_{t-k})$. We would like to find the stochastic process that governs the state transition in this model.

In addition to using our model in the context of market efficiency, we also consider applying it to predict liquidity risk, i.e. predict conditions that lead to a large bid-ask spread. (When the spread is large, the market faces a lack of liquidity, since it is impossible to trade close to the mid market price.)

References

[1] Frederic Abergel, Aymen Jedidi. A Mathematical Approach to Order Book Modeling. (January 14, 2011). Available at SSRN: http://ssrn.com/abstract=1740889

[2] Yakov Amihud, Haim Mendelson and Lasse Heje Pedersen. Liquidity and Asset Prices. Foundations and Trends in Finance Vol. 1, No 4 (2005) 269-364.

[3] Marco Avellaneda, Josh Reedy, Sasha Stoikov. Forecasting Prices from Level-I Quotes in the Presence of Hidden Liquidity. Forthcoming in Algorithmic Finance, http://algorithmicfinance.org, 2011.

[4] Jean-Philippe Bouchaudy, Marc Mezard, Marc Potters. Statistical properties of stock order books: empirical results and models. Quantitative Finance, Vol. 2, No. 4. (2002), pp. 251-256.

[5] Jean-Philippe Bouchaud, Marc Potters. Theory of Financial Risk and Derivative Pricing: From Statistical Physics to Risk Management.

[6] Chordia Tarun, Richard Roll and Avanidhar Subrahmanyam, 2005, Evidence on the Speed of Convergence to Market Efficiency, Journal of Financial Economics 76, 271-292.

[7] Rama Cont. Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance, volume 1 (2001), 223-236.

[8] Rama Cont. Statistical Modeling of High Frequency Financial Data: Facts, Models and Challenges (January 1, 2011). Available at SSRN: http://ssrn.com/abstract=1748022

[9] Rama Cont, Arseniy Kukanov, Sasha Stoikov. The Price Impact of Order Book Events. Working paper, 2011.

[10] Rama Cont, Adrien de Larrard. Price dynamics in a Markovian limit order market. Working paper, 2010.

[11] Rama Cont, Sasha Stoikov, Rishi Talreja. A Stochastic Model for Order Book Dynamics. Operations Research Vol. 58, No. 3, May-June 2010, pp. 549-563.

[12] Epps, Thomas W., 1979. Comovements in stock prices in the very short run, Journal of the American Statistical Association 74, 291-298.

[13] Sanford J Grossman, Merton H Miller, 1988. Liquidity and Market Structure. Journal of Finance, American Finance Association, vol. 43(3), pages 617-37, July.

[14] ??????????????????? Grossman Stiglitz ????????????????????

[15] Fama, Eugene (1970). "Efficient Capital Markets: A Review of Theory and Empirical Work". Journal of Finance 25 (2): 383417

[16] Thierry Foucault, Ohad Kadan, Eugene Kandel. Limit Order Book as a Market for Liquidity. Rev. Financ. Stud. (Winter 2005) 18 (4): 1171-1217.

[17] Thierry Foucault, Sophie Moinas, Erik Theissen. Does Anonymity Matter in Electronic Limit Order Markets? Review of Financial Studies, Vol. 20, No. 5, 2007.

[18] Refael Hassin, Moshe Haviv. To Queue or not to queue: equilibrium behavior in queueing systems. Kluwer Academic Publishers.

[19] Jasmina Hasanhodzic , Andrew W. Lo , Emanuele Viola. A computational view of market efficiency. Quantitative Finance, 11(7), 2011.

[20] Avner Kalay, Orly Sade, Avi Wohl. Measuring stock illiquidity: An investigation of the demand and supply schedules at the TASE. Journal of Financial Economics, Volume 74, Issue 3, December 2004, Pages 461-486.

[21] Longstaff, F. (1998). Optimal Portfolio Choice and Valuation of Illiquid Securities. Manuscript, Department of Finance, UCLA.

[22] Julian Lorenz, Jrg Osterrieder. Simulation of a Limit Order Driven Market. The Journal of Trading Winter 2009, Vol. 4, No. 1: pp. 23-30.

[23] Sergei Maslov. Simple model of a limit order-driven market. Physica A 278 (2000) 571-578.

[24] Sergei Maslov, Mark Mills. Price fluctuations from the order book perspective – empirical facts and a simple model. Physica A 299 (2001) 234-246.

[25] Marc Pottersa, Jean-Philippe Bouchaud. More statistical properties of order books and price impact. Physica A: Statistical Mechanics and its Applications Volume 324, Issues 1-2, 1 June 2003, Pages 133-140. Proceedings of the International Econophysics Conference.

[26] James M. Patell, Mark A. Wolfson. The intraday speed of adjustment of stock prices to earnings and dividend announcements. Journal of Financial Economics Volume 13, Issue 2, June 1984, Pages 223-252.

[27] Isabel Tkatch and Zinat Shaila Alam. Slice Order in TASE Strategy to hide? Working paper, 2007.

[28] I. Tkatch, E. Kandel. Demand for the Immediacy of Execution: Time is Money. Working paper, 2008.

[29] Rasika M. Withanawasam, Peter A. Whigham, Timothy Crack, I. M. Premachandra. An Empirical Investigation of the Maslov Limit Order Market Model. The Information Science Discussion Paper Series, Number 2010/04, March 2010, ISSN 1177-455X.

[30] Anil Bangia, Francis X. Diebold, Til Schuermann, John D. Stroughair. Modeling Liquidity Risk, With Implications for Traditional Market Risk Measurement and Management.

Table 1: Returns Autocorrelation

Resolution	Correlation Coefficient	P value
1 tick	-0.19	0
1 second	-0.28	0
2 seconds	-0.27	0
3 seconds	-0.27	0
5 seconds	-0.26	0
10 seconds	-0.23	0
20 seconds	-0.19	0
30 seconds	-0.16	0
40 seconds	-0.16	0
1 minute	-0.11	0
2 minutes	-0.07	0
5 minutes	-0.07	0
10 minutes	-0.07	0
15 minutes	-0.04	3.88E-05
20 minutes	-0.03	0.007
30 minutes	-0.03	0.051
40 minutes	-0.04	0.003
50 minutes	-0.04	0.001
1 hour	0.01	0.5
2 hours	-0.03	0.246
3 hours	-0.01	0.783

Table 2: Mean Absolute Returns for Various Time Horizons

Resolution	Mean Absolute Return
1 tick	0.00076
1 second	0.00075
2 seconds	0.00075
3 seconds	0.00075
5 seconds	0.00075
10 seconds	0.00076
20 seconds	0.00077
30 seconds	0.00079
40 seconds	0.00080
1 minute	0.00085
2 minutes	0.00098
5 minutes	0.00127
10 minutes	0.00162
15 minutes	0.00188
20 minutes	0.00210
30 minutes	0.00242
40 minutes	0.00247
50 minutes	0.00240
1 hour	0.00322
2 hours	0.00423
3 hours	0.00633

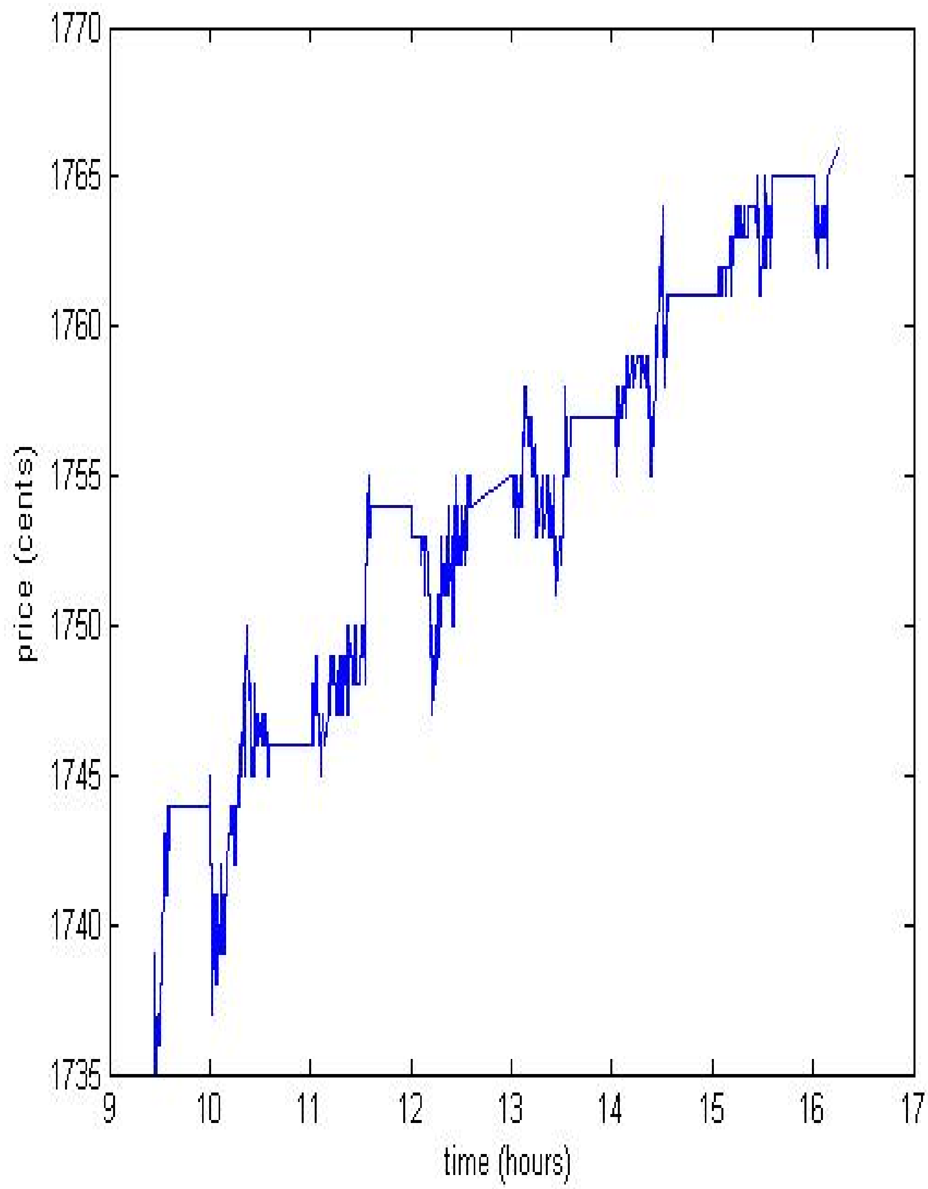

Figure 1: Price process for the Bank Leumi stock for one day: 2010/01/03 (one tick resolution)

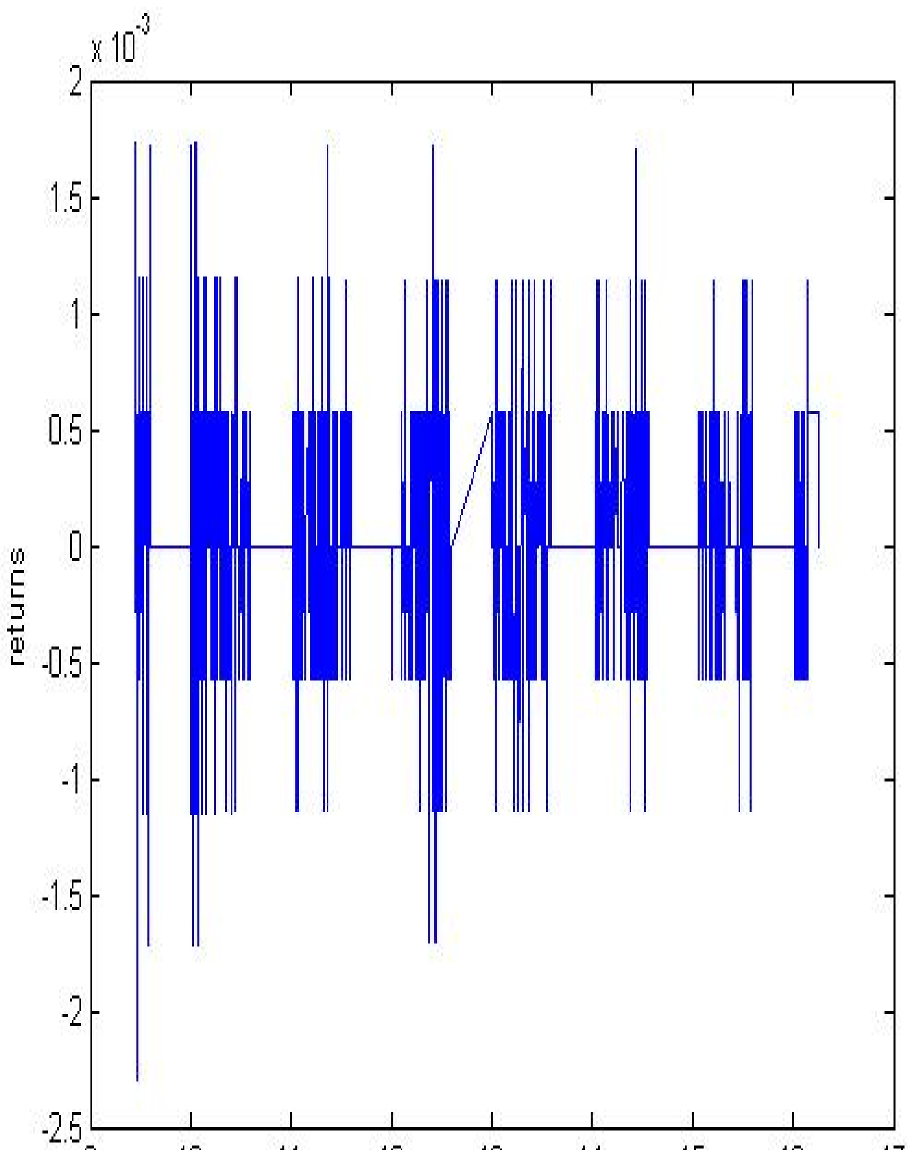

Figure 2: Returns process for the Bank Leumi stock for one day: 2010/01/03 (one tick resolution)

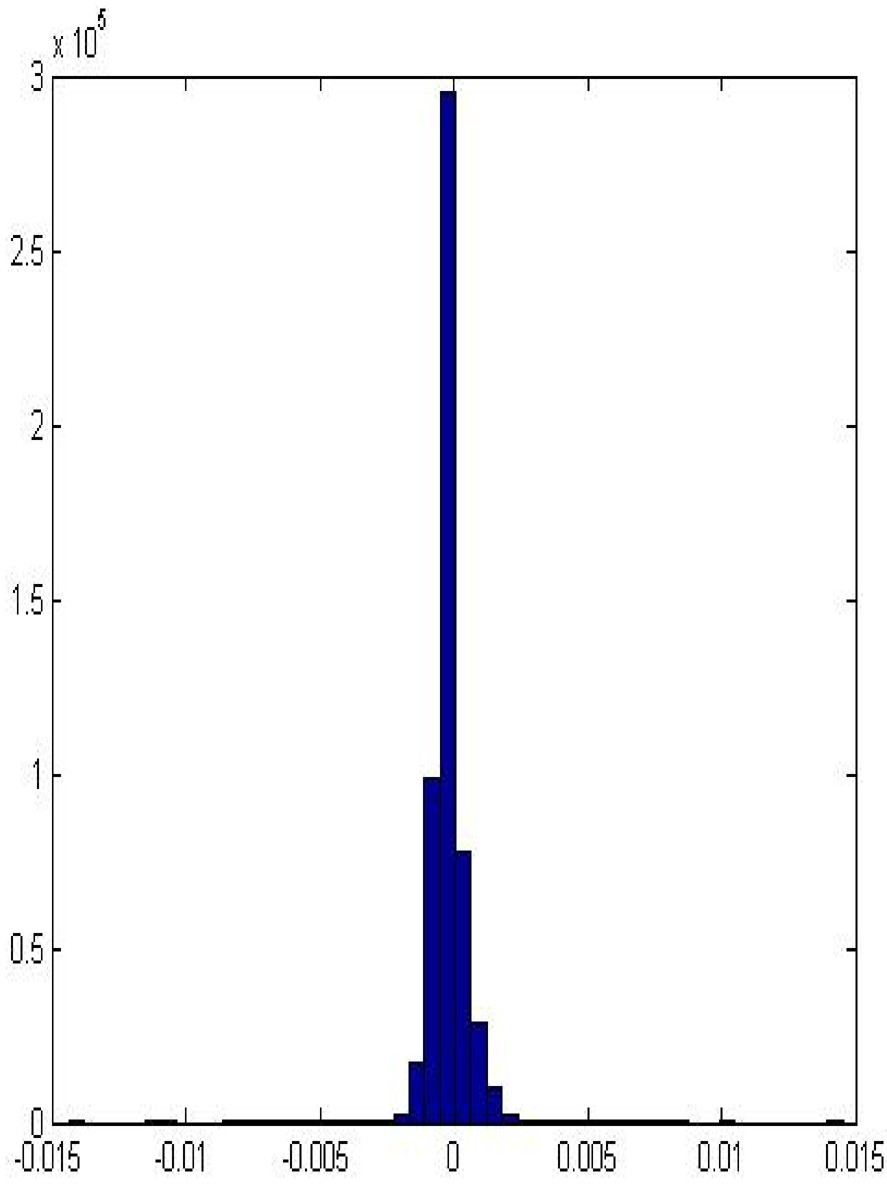

Figure 3: Returns distribution for the entire year (one second resolution)

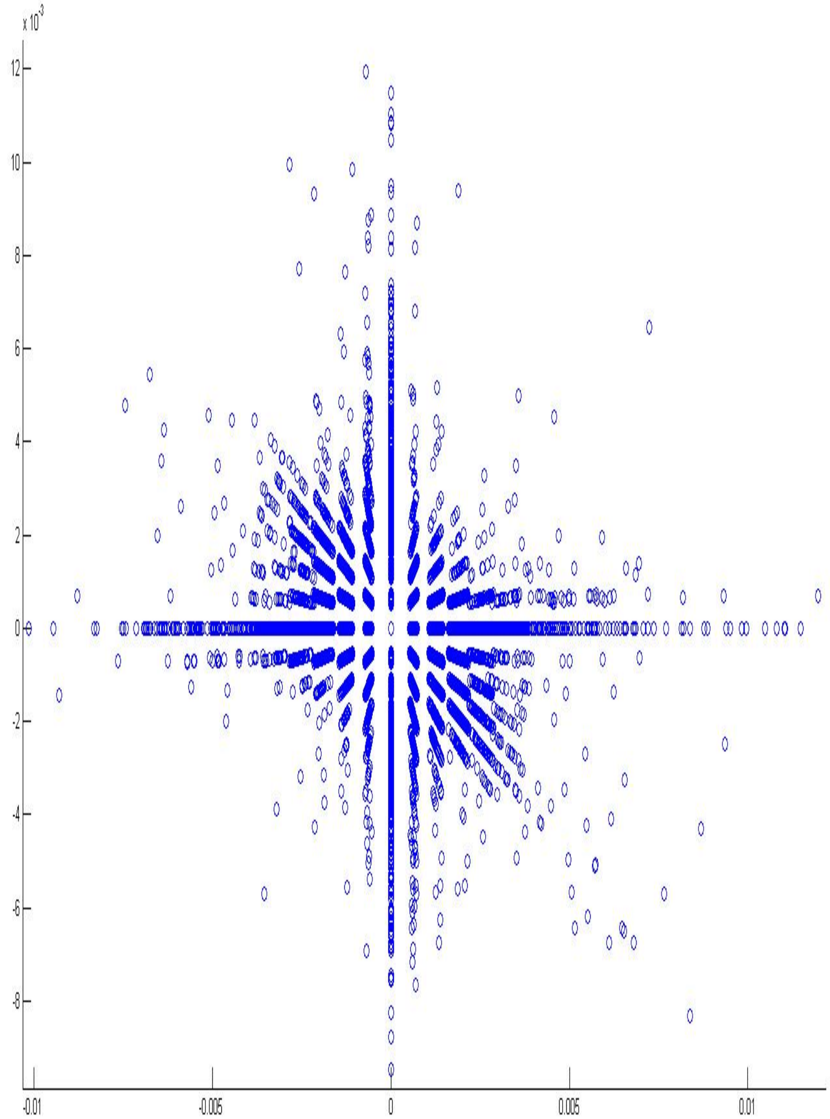

Figure 4: Returns autocorrelation for the entire year (one tick resolution)

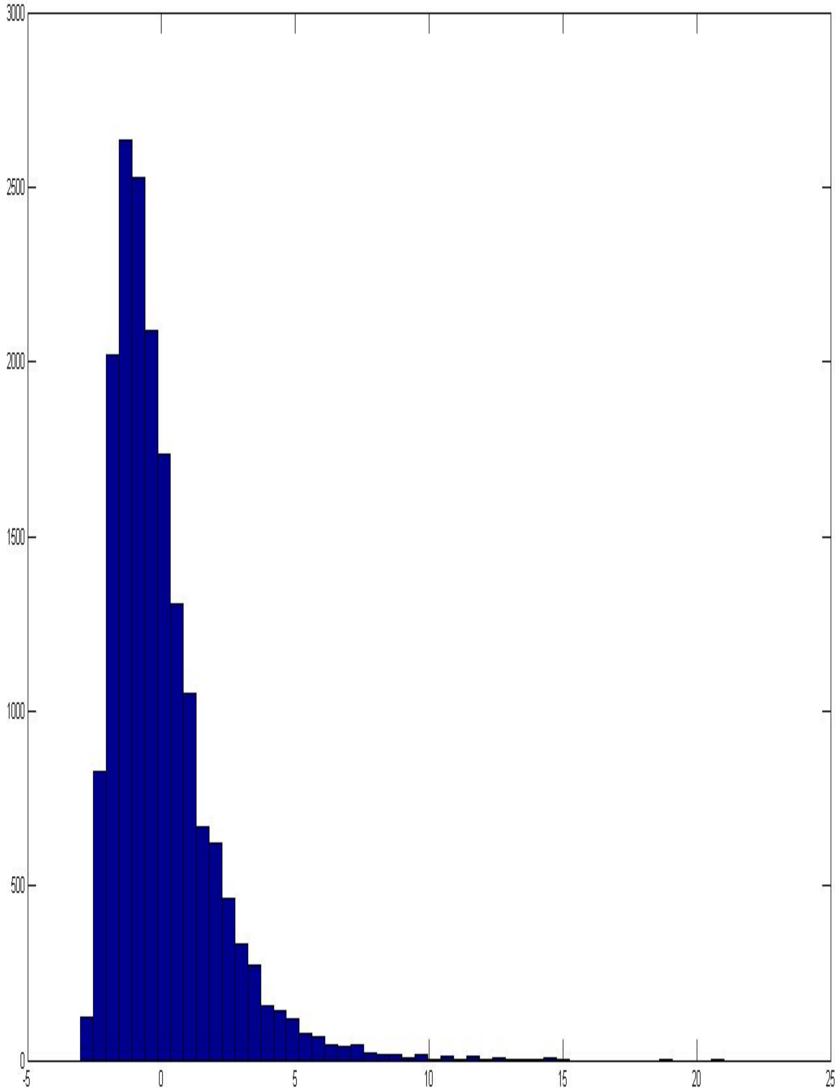

Figure 5: Trading intensities distribution for the entire year (normalized by hour of day)