

DO UKRAINAIN ANALYSTS
AFFECT STOCK PRICES?

by

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Abstract

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The Ukrainian stock exchange is evaluated for efficiency based on its reaction to secondary dissemination of analytical forecasts. A significant reaction to buy and hold recommendations is observed, suggesting the market to be inefficient in the sense of the semi-strong and strong formulations of the EMH. Furthermore, the study also points towards the lack of robustness in conventional abnormal return measures and the possibility of a reputational effect, which may offer a reason for why inefficiencies tend to arise.

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INTRODUCTION

The question of whether financial markets are efficient has been the subject of much economic research. It has become a tradition to distinguish between three different forms of the so-called Efficient Market Hypothesis (EMH): the weak, the semi-strong, and the strong. The weak EMH essentially states that it is impossible to forecast returns by relying on historical patterns (stocks that do well today will not necessarily do well tomorrow), the semi-strong form says that markets incorporate public information rendering such information useless for predictions. Finally, the strong form says that financial markets are completely efficient and that it is impossible to systematically earn profit based on any information: either public or private.

Much research has been done to test either one of these forms. Although a plethora of evidence suggests that past prices are unlikely to be useful for forecasts and that the weak EMH is most likely a good assumption (Berneburg, 2004), informational efficiency is currently a subject of heated academic debates. While the existence and popularity of investment advisory agencies seems to suggest that the market can be predicted via publically available information¹, the fact that professional investors have not been able to outperform market indexes raises doubt about the usefulness of such forecasts (Malkiel, 2005).

Empirical studies concerning market efficiency have been done for over forty years. While in the 1970's and the beginning of 1980's the EMH found quite a bit

¹ Such agencies are bound by law to use public information exclusively, as using insider information can lead to market abuse

of support (Ball et al., 1978), the 1990's brought about discoveries of market phenomena that seem to go against it. These include such anomalies as the well known January Effect (Bhardwaj et al., 1992), the Value Line Enigma (Stickel, 1985), and even the Weather Effect (Hirshleifer et al., 2001), among others. In light of such evidence, efficiency has begun to lose its unwavering hold, and the academic community has effectively been split up into those who believe and those who distrust the hypothesis.

This study provides new evidence to the debate concerning market efficiency. While there has been a lot of research on the subject in North America, only a few works have actually concerned themselves with data from other parts of the world². The Ukrainian market in particular has only been tested for efficiency in a couple of studies and only one of them has been able to make a claim about the semi-strong form. Dedov (2000) has tested the PFIS for random walk patterns and Pavlenko (2008) for mean-reversion, both of which deal with the weak form of efficiency. Moskalenko (2005) is practically the only one who has attempted to test the Ukrainian stock market for sudden releases of new information, yet his methodology is too dependent on being able to make an exhaustive list of major economic and political events, which makes misspecification extremely likely. The study at hand offers a completely different approach to examining informational efficiency. It draws its theoretical background from the work of Latham (1986) and tests directly whether abnormal returns are formed by secondary releases of information.

² Evidence from different markets is crucial given the limited robustness of most efficiency studies

Chapter 2

The literature review begins with an intuitive introduction to market efficiency. It is followed by a chronological description of development of economic thought on the subject, which leads to a rather strict theoretical definition that is central to the research. Beginning with a generalized overview of empirics, three distinct strands of empirical work are then discussed in some detail, with the focus on second-hand dissemination. Finally, the research at hand is placed into the context of preceding literature and its contribution to the EMH debate is highlighted.

LITERATURE REVIEW

It is probably safe to assume that stock market prices are affected by macro and microeconomic factors, as equities are simply “pieces” of different firms in a given economy. Changes in these factors lead to fluctuations of expected profits and thus stock prices. Intuitively, it would seem that if one were able to predict the movement of economic variables, one would be able to predict future stock prices and thus earn profit. The problem with this argument is that in order to gain through trading, one has to not only successfully forecast the future, but he has to also do it “quicker” than the market. In other words, if at t_0 an individual knows a certain stock price to be p_t at time t and the market possesses the same information, p_0 will adjust so that buying stock today at p_0 is the same as buying it at p_t at time t . Thus somewhat loosely, an efficient market with respect to an information set θ will prohibit any economic profits³ through trading based on θ .

³ Economic profits are defined here as risk adjusted returns net of all costs.

Although seeming intuitively simple, the idea of an efficient market has a very long history of definition. While theoretical works on the subject date as early as the beginning of the twentieth century (Bachelier, 1900), the idea has received its conceptual framework from a now recognized theory of rational expectations, first developed by Muth in 1961. Muth reasoned that if agents are rational and information is costless, then agents form expectations in such a way that they utilize all available information to make the best guess possible. Mathematically, this would mean that if $f(p_t|\theta_{t-1})$ is a distribution of prices at time t conditional on the information set θ_{t-1} , then the expectation of rational agent is given by

$$E(p_t|\theta_{t-1}) = \int_a^b p_t f(x_t|\theta_{t-1}) dx_t$$

Moreover, the forecasting error, defined as $\varepsilon_t = p_t - E(p_t|\theta_{t-1})$ has the properties of (1) having an expected value of zero⁴ conditional on θ_{t-1} and (2) being uncorrelated with the information set itself⁵. In 1970 Fama applied the idea of rational expectations to formalizing what an efficient market with respect to an information set actually is. He based his discussion on the idea of rational arbitrageurs, who, if present in the market, would quickly (instantaneously with no transaction costs) drive the price to a level that “fully reflects all available information”⁶ (Fama, 1970). He was also the first to classify information as “public” or available at zero cost, and “private”, which comes at expense. Although by arguments concerning rationality and arbitrage it can be demonstrated that information that is practically costless to market participants is likely to be reflected in market prices, it seems difficult to believe that private information cannot be used for profit. Fama argued, however, that since only a

⁴ $E(\varepsilon_t|\theta_{t-1}) = 0$

⁵ $E(\varepsilon_t \theta_{t-1}|\theta_{t-1}) = 0$

⁶ Fama later restated this formulation by inserting that prices in an efficient market have to “fully reflect all available information correctly” (Fama E., Foundations of Finance, 1976)

sufficient number of investors is needed to eliminate arbitrage, there is very little information that is truly private⁷.

The definition of market efficiency was later refined by Latham (1986), who argued that Fama's definition, though being intuitive, was in fact "empty and tautological," as it gave no way of testing efficiency in practice. Latham argued that one could never compare real prices to those that "fully reflect information", since one is not presented with data from an ideal world with an efficient market. He therefore argued that a better definition of efficiency would be that "the market is efficient with respect to an information set if revealing it to all agents would change neither equilibrium prices nor portfolios" (Latham, 1986). The major contribution of Latham's definition lies in the fact that it possesses a "subset quality," meaning that if the market is shown to be inefficient with respect to a subset of an information set it is also shown to be inefficient with respect to the set itself. This means that one need no longer compare actual prices to those containing "all available information" to disprove the strong EMH, he need only to show that prices in the market change when certain information is disclosed and failure of the strong EMH logically follows. The idea of this research is to apply exactly this kind of reasoning.

Although much of the early empirical literature has been devoted to testing the weak form of the EMH (Samuelson, 1965), the fact that past prices are bad forecasters of future prices has been more or less accepted by the academic community⁸. The body of the regression analysis for the past thirty years has thus concentrated on examining the semi-strong form of the hypothesis. The ideas behind most of this research can be split into three main categories: (1) examining

⁷ This argument is practically the grounds for the strong EMH

⁸ Some authors, however, still contest this (Al-Loughani & Chappell, 1997)

whether new information is quickly incorporated into market prices, (2) examining whether the market responds to purely cosmetic events (such as stock splits), and (3) examining whether the market responds to “old” information. While early empirical literature has found much general evidence in support of market efficiency (Ball et al., 1968), the idea has begun to find opposition in the late 1970’s (Lakonishok et al., 1979) and early 1980’s (Bjerring et al., 1983). Among works which demonstrate abnormal market reactions to stock splits (Watts, 1987), the past two decades have also brought about such inexplicable anomalies as the well known January Effect (Bhardwaj et al., 1992), the Value Line Enigma (Stickel, 1985), and the Weather Effect (Hirshleifer et al., 2001). While these effects do cast a shadow of doubt on the EMH, the academic community is reluctant to offer a viable alternative which would not only explain the market in a better way, but also incorporate all of the criticism. While some economists tend to think that the rapidly developing area of behavioral finance is already a rival to efficiency, the new theory has yet to offer a model that holds up in more than a few empirical studies (Fama E. , 1998).

Probably the most prolific strand of economic literature on the subject of the EMH deals with the market reaction to new information. Theoretically, an efficient market should incorporate news instantaneously if transaction costs are zero. Because in practice transaction costs are nonzero and trading takes time, most researchers try to test whether information is incorporated “quickly”⁹ into market prices. Quite expectedly, evidence on the subject is rather mixed. While some authors find that prices adjust to earnings announcements (Ball et al., 1968) and credit rating changes (Weinsten, 1977) within a day, others report that adjustment is in fact slow enough for a profit possibility to exist (Grier et. al, 1976).

⁹ Quickly enough so that it is impossible to make profits

Another strand of empirical research deals with how the market reacts to purely cosmetic events or events containing no or very little information. Interestingly enough, a number of authors find that events such as stock splits (Wulff, 2002) and inclusion to the S&P 500 Index (Shleifer, 1986) produce positive abnormal returns. Proponents of the EMH have attempted to explain such findings with signaling theories, explaining that stock splits, for example, although cosmetic at first glance may actually act as valuable signals to traders (Ikenberry et al., 1996). Nonetheless, events such as sunny weather, which has been found to be associated with positive returns (Hirshleifer et al., 2001), are yet to be given a viable explanation.

The strand of research most pertinent to this work deals with the market reaction to “old” information. Theoretically, an efficient market should not react to news that have already been previously announced and generally to information that is known to a large number of traders. Predictable macroeconomic indicators, such as GDP growth, should theoretically produce no abnormal returns, while factors with very unpredictable components, such as monetary fluctuations, may in theory be able to catch market agents “by surprise”. Empirically, support for such results has been found in the works of Chen et al. (1986), Pearce et al. (1985), and others. Not surprisingly, other authors have found evidence that contradicts such findings. Wasserfallen (1989) has shown that any effect of macroeconomic news on the British, German, and Swiss stock markets is likely to be very small or nonexistent.

Intuitively, one of the best ways to test how markets respond to old information is to examine reaction to events that consist of information sets being released to the market for a second time. One application of this methodology can be found in studies dealing with second-hand dissemination of analytical reports.

Proponents of the EMH have criticized investment advisory agencies for over forty years, as these organizations seem to publish predictions based on publically available information, something that from the point of view of efficiency should be practically useless. Nonetheless studies have reported again and again that markets do react to stock forecasts (Stickel, 1985), meaning that marketes are either inefficient, or that brokerage houses acutally do provide useful information to investors. While the latter of the two conclusions may be correct¹⁰, efficient market should still not react to a secondary releases of such information, as investment advyce should have already been reflected in the prices after primary publications. In other words, forecasts that have already been received by a group of traders on the market should in theory, accroding to Latham, change neither equilibrium prices nor portfolios the second time they are announced.

The pioneering empirical work in second-hand dissemination has been done by Davies and Canes in 1978. In their research the authors examine abnormal return formations following publications of investment advice in the “Heard on the Street” column of the *Wall Street Journal*. David and Canes argued that, for obvious reasons, financial analysts are careful to distribute their predictions to direct clients usually at least a week before their reports appear in the newspaper, making “Heard on the Street” a second-hand source of information. Using an event-study methodology coupled with the Market Model, the authors found statistically significant positive abnormal returns following overall buy recommendations and negative abnormal returns following overall sell recommendations. Using a longer period of data the same results were corroborated by Liu et al. in 1990, but were dismissed by Beneish in 1991. Nonetheless, results similar to those of Davies and Canes were confirmed by more recent works of Barber & Loeffler (1993), who worked with the

¹⁰ Investment analysts may provide useful and sophisticated analysis of public information to create something that is no longer public

“Dartboard” column of the *Wall Street Journal* and Han & Suk (1996), who examined publications in the *Barron’s* “Research Reports” column.

Although highly valuable empirically, this sub-strand of EMH research has its faults. While having a good theoretical background, most studies suffer from methodological problems as (1) event studies are a relatively recent phenomenon and (2) the Market Model, which is based on the CAPM, has no proof of being correctly specified. The problem is aggravated even more by the fact that almost all such studies have been done using data from the NYSE, meaning that robustness of any results has been left practically unverified. The research at hand attempts to remedy this gap by providing additional insights into usefulness of different abnormal return measures for a stock market very different from that of the United States. Furthermore, the work examines the presence of a reputational effect that may shed light on why abnormal returns may form in the first place.

Overall, the Efficient Market Hypothesis has seen quite a bit of development both theoretically and empirically over the past fifty years. It has come from almost general acceptance in the 1970’s to harsh criticism in the late 1980’s and early 1990’s, supplied by strange excess returns and anomalies such as the Value Line Enigma. As a result, the academic community has found itself at the midst of a battle between supporters and critics of the EMH. It seems that the research at hand could not have found a better timing, as it carries potentially valuable evidence from a very different stock market, which can help add to the robustness of the results in the field.

DATA DESCRIPTION

The initial sample consists of 2,253 recommendations made by 87 different analysts from 16 brokerage houses and published on Bloomberg over the period February 2st, 2005 through December 1st, 2008. Because Bloomberg is a database available to millions of subscribers, Ukrainian analysts publish their reports approximately two weeks after initial dissemination to their direct clients¹¹, which means that Bloomberg acts much like the “Heard on the Street” column of the *Wall Street Journal*. Out of the 283 stocks listed on the PFTS Exchange, recommendations were made for 117. The recommendations themselves initially came in 10 different varieties because of Millennium Capital, which instead of using the usual 5 point scale (strong sell through strong-buy), used its own scale and names (a 6-point scale of reduce through accumulate). After Millennium Capital’s recommendations were made comparable with the rest of the sample¹², the number of distinct observations came down to four, as “strong sell” was never recommended by any of the analysts. Descriptive statistics are provided in Table 1.

Table 1 Descriptive statistics for the overall sample of recommendations

	Observations	Percent of total
strong-buy	76	3.37
buy	1,119	49.62
hold	590	26.16
sell	470	20.84

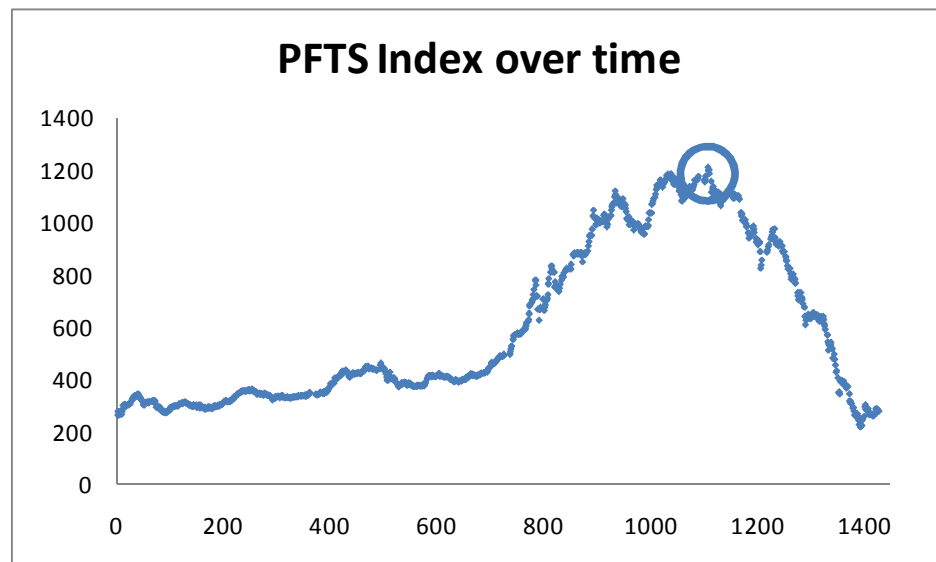
¹¹ There is no data available on the exact dates of initial publications, as Ukrainian brokerage houses don’t give out such information. After interviewing some of the workers in such companies, it was concluded that publications happened approximately two weeks prior to being submitted to Bloomberg

¹² “speculative buy” was turned into “strong-buy”, “accumulate” and “outperform” were transformed into “buy”, “market perform” was replaced with “hold”, “reduce” turned into “sell”

Noteworthy is the fact that “buy” recommendations are much more common than “sell” recommendations (they occur 3.4 times as frequently), which means that generally analysts perceived stocks on the PFTS to be undervalued.

It is also of interest to examine the market index (the PFTS index) graphically, as our data contains a period of growth and a very distinct period of decline. The periods are easily distinguished by looking at Figure 1.

Figure 1 PFTS index over time



The period of growth can roughly be defined as starting at time 0 (February 2nd, 2005) and ending at the maximum point, which occurs on day 1108 (January 15th, 2008). The period of decline starts at the maximum point and ends on day 1427, which is the last day of the dataset. It should be noted that such an index picture is not commonly found in developed markets, which is one reason why the PFTS presents empirical interest.

Another distinguishing feature of the Ukrainian securities market is that stocks on the PFTS are characterized by somewhat thin, but very volatile trading patterns. Stock volatility and average return percentiles for the sample are available in Table 2.

Table 2 Stock volatility percentiles

Percentile	Return (%) SD	Average Return (%)
1%	1.603	-0.00418
5%	2.730	-0.00323
10%	3.244	-0.00173
25%	4.317	-0.00082
50%	5.539	0.000113
75%	6.984	0.001244
90%	10.506	0.002139
95%	12.818	0.002665
99%	16.678	0.00311

One can observe that for approximately 50% of the stocks 1 standard deviation is a 5.54 % daily return. For some stocks, however, a standard deviation can be a 12% or even 16%. While these numbers are by no means low, on trading days even the least volatile stocks experience immense price jumps. A rather clear example of this is the Odessacabel stock, which has the lowest overall standard deviation of the sample (1.232 %). Odessacabel's stock becomes over 16 times more volatile if its volatility is computed only over days that it is traded.

Concerning average stock returns it should be noted that because of the decline period, the stock market as a whole has a very small average return. According to the table, the median of the sample is characterized by a return of 0.01%. In fact, 25% of all stocks actually have negative return values.

METHODOLOGY

The Basic Approach

Because an efficient market does not react to secondary dissemination of information, the goal of the methodology is to set up a way to examine the market response to recommendations which have been published in the Bloomberg database. The standard approach in literature to measuring market reactions is by using event-study analysis. The basic idea behind all such strategies is to test whether the process under examination exhibits abnormal behavior when a certain event is triggered. Let us define the return of security i at time t as

$$R_{i,t} = \ln\left(\frac{p_{i,t+1}}{p_t}\right)$$

where $p_{i,t}$ is the stock's price at time t .

One can treat analyst publications in Bloomberg as events, triggered at certain periods of time, which may or may not affect stock returns. Because one can only observe outcomes that have already been affected by events, some sort of benchmarking is needed to detect abnormality. This research will use two different excess return measures: the OLS Market Model and Mean Adjusted Returns.

The OLS Market Model

The OLS Market Model approach uses a variation of the Capital Asset Pricing Model (CAPM) to predict “normal” returns. According to the CAPM, the expected return of asset i is given by:

$$E(R_i) = E(R^f) + \beta_{im}(E(R_m) - E(R^f))$$

where R^f is the risk-free rate of return, R_m is the return of the market portfolio, and β_{im} is given by

$$\beta_{im} = \frac{cov(R_{it}, R_{im})}{var(R_m)}$$

Assuming the risk-free rate to be constant over time, the model can be re-written as

$$E(R_{i,t}) = \alpha_i + \beta_i E(R_{m,t}),$$

where $\alpha_i = R^f - \beta_i R^f$.

The main advantage of the Market Model approach is the theoretical background from which it is derived. Unfortunately, although looking quite simplistic, the above equation is in fact very difficult or even impossible to estimate correctly, as the market portfolio can in principle include not only financial assets such as stocks and bonds, but also durable goods, real estate, and even human capital (Fama & French, 2004). Most empirical research in finance, however, is forced to assume the market portfolio to be an index of the financial market under consideration, as broader measures are often unavailable. This research will consider two alternative measures to fulfill the role of the market portfolio: the PFTS index and an equally-weighted index of all stocks available via Bloomberg. While the first choice is rather standard in the literature, it is unclear that such an index reflects the Ukrainian stock market as a whole, as it consists of only 20 stocks. The latter choice is simply the broadest possible daily index that can be obtained with the available data.

In the Market Model we thus define abnormal returns as

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t})$$

Denoting the event day as 0, the parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated over an estimation period of 100 days, from day -1 to day -100 .

Mean Adjusted Returns

The Mean Adjusted Returns model assumes the expected return for security i to be constant over the period of estimation (100 days, as in the Market Model):

$$E(R_i) = K_i$$

This approach is also in line with the CAPM under the assumption that securities have constant systematic risk and that the efficient frontier is stationary. Although clearly having its own downsides, mean adjusted returns do not rely on a measure of the market portfolio, which is the biggest flaw of the Market Model.

In this case the abnormal return $AR_{i,t}$ can then be defined in a similar manner:

$$AR_{i,t} = R_{i,t} - K_i$$

Again, denoting the event day as 0, K_i is estimated over an estimation period of days 100 days (-1 to -100).

Analysis of Abnormal Returns

There are two basic ways for evaluating abnormal returns: the average abnormal return (\overline{AR}), and the cumulative average abnormal return (\overline{CAR}). Whereas the \overline{AR} measure shows the abnormal return on a certain day after the event has occurred, the \overline{CAR} measure shows the cumulative effect over all days up to a certain point after the occurrence. Following the methodology of Liu et al. (1990), for N securities the average abnormal return at time t and the cumulative average abnormal return on a time-band $[T_1, T_2]$ are defined respectively as:

$$\overline{AR}_t = \frac{1}{N} \sum_{i=1}^N AR_{i,t}$$
$$\overline{CAR}_{T_1, T_2} = \sum_{t=-T_1}^{T_2} \overline{AR}_t$$

Where T_1 and T_2 are the beginning and the end of the event period respectively. This research will fix T_1 at 0, although some literature has considered the event period to start prior to this day in order to consider price adjustments that reflect market anticipations.

To test the significance of \overline{AR}_t and $\overline{CAR}_{T_1, T_2}$ one has to construct a test statistic.

It is helpful to define a standardized abnormal return, $SAR_{i,t}$ as:

$$SAR_{i,t} = \frac{AR_{i,t}}{SD_i}$$

where SD_i is standard deviation of abnormal returns calculated over the 100 days¹³

Next, under the assumption that the $AR_{i,t}$ are independently identically distributed with finite variance, $SAR_{i,t}$ are also independently distributed random variables with mean 0 and variance 1. One can thus define the average standardize abnormal return \overline{SAR}_t and the standardized cumulative abnormal return, $\overline{SCAR}_{T_1, T_2}$, as:

$$\overline{SAR}_t = \frac{1}{N} \sum_{i=1}^N SAR_{i,t}$$

$$\overline{SCAR}_{i, -T_1, T_2} = \frac{1}{N} \sum_{i=1}^N \frac{\sum_{t=T_1}^{T_2} SAR_{i,t}}{(T_2 - T_1 + 1)^{1/2}}$$

In the absence of abnormal behavior and under the assumption of independent identical distributions of abnormal returns, the test statistic for a sample of N securities on day t , $\tau(T_2)$ and the test statistic for the time band $[T_1, T_2]$ should follow a t-distribution with 99 degrees of freedom¹⁴, where

¹³ In fact the exact formula depends on the amount of days included in the estimation period of the coefficients, but it equivalent to the standard deviation of the error term if the number of days is large enough

¹⁴ The SD_i was estimated over 100 days. One degree of freedom is lost while demeaning

$$\tau(T_2) = \overline{SAR}_t \left(N^{\frac{1}{2}} \right)$$

$$\tau(T_1, T_2) = \overline{SCAR}_{T_1, T_2} \left(N^{\frac{1}{2}} \right)$$

The one-sided significance test is used for all recommendations except for hold.

The Generalized Sign Test

Although variations of the τ -statistic are used everywhere in efficiency research, all such measures suffer from possible violations of assumptions that are likely to happen in real data. For one, abnormal returns can fail to follow a normal distribution and can even be dependently distributed. For this reason many event studies typically report a nonparametric test, which can sometimes detect misleading results. Typically researchers report either the rank test or the sign test, depending on the data. Cowan (1992) has shown that the generalized sign test is preferred to the rank test for samples with thinly traded stocks or large variance increase during event times. Most stock data on PFTS has exactly these characteristics, as the market is rather small.

The idea of the generalized sign test is to check whether the number of stocks with positive (or negative) abnormal returns in the event window exceeds the number expected in the absence of abnormal performance. The expectation is based on the fraction of the sought returns in the 100 day estimation period,

$$p = \frac{1}{N} \sum_{j=1}^N \frac{1}{100} \sum_{t=-100}^{-1} S_{i,t}$$

where for buy recommendations

$$S_{i,t} = \begin{cases} 1, & AR_{i,t} > 0 \\ 0, & \text{otherwise} \end{cases}$$

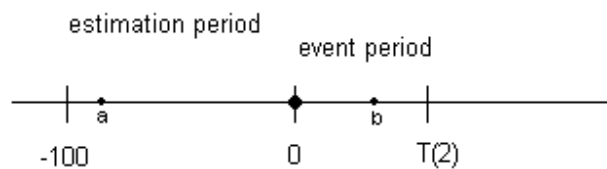
The test statistic uses normal approximation to the binomial distribution with parameter p . Setting the number of stocks for which $\overline{SCAR}_{-T_1, T_2} > 0$ (all signs are reversed for sells) to be equal to w , the generalized sign test statistic becomes

$$Z_{ST} = \frac{w - Np}{(Np(1 - p))^{\frac{1}{2}}}$$

Correcting for event clustering

One of the biggest sources of bias in event studies can come from the presence of other events either in the estimation period (where normal returns are defined) or the event period (where the market reaction is measured). Figure 2 illustrates the problem graphically

Figure 2 The Problem of Event Clustering



If the event of interest, for example a buy recommendation, occurs at day 0, then if another buy recommendation also occurs either at on day a or day b , the market reaction in the event period is likely to be too high¹⁵. In order to avoid such biases, this study will only consider those events that contain no other recommendations from time -100 to T_2 . Of course such strict restriction cut the

¹⁵ It may also be too low if a buy happens at point a , because “normal returns” might be too high, but this will largely depend on how far away day a is from day 0

sample size by approximately a factor of 5, but this is still enough to check for statistical significance.

Abnormal Return Distortions

As already mentioned, there is no perfect way of measuring abnormal returns, which is one reason why market efficiency still remains an unanswered question. While the literature has a few standard approaches, it is unclear that these measures work well for Ukrainian data, as its stock market is characterized by sharp price movements and thin trading patterns the likes of which are not present in the NYSE or other developed exchanges. The mean adjusted returns methodology, for example, will show positive abnormal returns if stock prices rise very sharply, as the average stock return over the estimation period and the event period will differ even in absence of any events. Theoretically, the market model should be able to correct for market tendencies, yet its dependence on the market index is so heavy that its abnormal returns may also be distorted. While authors that base their analysis on the NYSE claim that the results of their studies are generally insensitive to the definition of abnormal returns,¹⁶ there is no guarantee that the same holds for the PFTS.

One way to assess how well different abnormal return measures work for Ukrainian data is to examine how well they deal with randomly simulated events. As on average random fictitious events will not coincide with real events, good methodologies should show no market reaction. Using Matlab's rand command¹⁷, two series of random integers are generated using a uniform distribution; one

¹⁶ Stickel (1995) for example

¹⁷ Seed number 1986

between 1 and 117 and the other between 1 and 961¹⁸. Together the two vectors create a database of stocks and times of fictitious randomly generated events. It should also be remarked that in this case there is no need to correct for event clustering, as the events themselves are not real and clustering has no effect on either the estimation or the event period.

¹⁸ The number of total days is 1427, but the number of trading days is 961. All data has been converted to trading days in order to avoid zero returns on non-trading days, as these may show up like market reactions

RESULTS

Picking the Best Abnormal Return Measure

Table 3 provides the sample-wide market reaction displayed by different methodologies to randomly simulated fictitious events (only $\tau(T_1, T_2)$ statistics are provided). A two-sided hypothesis is used to measure significance, as the null hypothesis is that there is no market reaction. As no corrections are needed for event clustering, the number of observations is never a problem. All data is converted to trading days (weekends are taken out) for this and other sections of the analysis.

Table 3 Overall market reaction over the whole sample by methodology to randomly generated events

	<i>MMp</i>	<i>MMpST</i>	<i>MAR</i>	<i>MARST</i>	<i>MMeq</i>	<i>MMSTeq</i>
$\tau(0,1)$	0.1082	0.58875	-0.014004	-0.34668	-0.30109	0.98139
$\tau(0,2)$	-0.53342	-0.20563	-1.1893	-0.14933	0.12475	1.3117
$\tau(0,3)$	-1.1409	0.325	-1.9137*	0.11509	1.0565	2.0409
$\tau(0,4)$	-1.6116	0.77092	-2.6167**	-0.1006	0.75279	1.2961
$\tau(0,5)$	-1.8711	1.4858	-3.067***	0.027152	-0.34947	0.69611
$\tau(0,7)$	-2.7449	1.0219	-4.1995	-0.1053	-0.80433	0.76235
$\tau(0,10)$	-3.6316***	0.95905	-5.6678***	0.023229	2.1786**	1.3523
$\tau(0,15)$	-3.305***	0.98916	-5.4486***	-0.55785	2.0207**	0.17246
$\tau(0,20)$	-3.983***	-0.67023	-6.3121***	-1.6359	3.814***	0.96631
$\tau(0,25)$	-4.4724***	-0.64497	-7.2925***	-2.0846**	5.3019***	2.0644**
$\tau(0,30)$	-4.7635***	-0.39502	-7.7765***	-1.8454*	5.6013***	1.7135*
$\tau(0,35)$	-4.3443***	0.10549	-7.7706***	-2.1783**	2.7762***	2.0046**
$\tau(0,40)$	-4.5595***	0.55351	-8.1848***	-1.9629*	1.9515*	2.0959**

The statistics are to be read as follows: *MMp* stands for the estimation done with the Market Model and the PFTS index, *MAR* stands for the estimation done with

the mean adjusted returns methodology, *MMeq* stands for the Market Model with the equally weighted index; *MMpST*, *MARST*, and *MMSTeq* are their respective generalized sign tests. Values significant at 1% are marked with three stars, those that are significant at 5% are marked with 2 stars, and those significant at 10% are marked with 1 star.

The above table suggests that all measures are culpable of yielding abnormal returns when none are present, especially over event periods of 25 days and longer. Whereas both the Market Model with the PFTS index and the mean adjusted return methodology tend to overestimate normal returns, the Market Model with the equally weighted index tends to underestimate them. The exact reason behind such distortions is not completely clear, but they are likely due to a combination of sharp market movements, a lack of the real market portfolio, and thin trading patterns¹⁹. The mean adjusted returns methodology seems to be the worst measure here, as it starts to show significant abnormal returns as early as 3 days after event date. It is overall rather surprising to see how easily standard event-study approaches fail in a non-conventional stock market setting.

As the dataset can be effectively spit up into two very different time periods, it is also of interest to see which measures do better period-wise. The results are provided in tables 4 and 5.

¹⁹ Thin trading patterns tend to provide a small number of nonzero observations in the estimation period, making it difficult to measure α and β very accurately

Table 4 Market reaction during the growth phase (pre 15/01/08) by methodology to randomly generated fictitious events

	<i>MMp</i>	<i>MMpST</i>	<i>MAR</i>	<i>MARST</i>	<i>MMeq</i>	<i>MMSTeq</i>
$\tau(0,1)$	0.72958	0.59111	0.88098	0.72738	-1.5325	1.6169
$\tau(0,2)$	-0.071732	0.65418	-0.086898	1.7122*	-0.73984	2.0945*
$\tau(0,3)$	1.0673	1.2652	1.0355	2.417**	0.43979	2.8794**
$\tau(0,4)$	0.12986	1.3164	-0.08055	2.5705**	-1.2192	2.0098*
$\tau(0,5)$	-0.49353	1.6111*	-0.62534	2.6562***	-1.8697*	1.3365
$\tau(0,7)$	-0.026394	1.6111*	-0.28624	2.9134***	-0.44867	2.0188*
$\tau(0,10)$	-0.71671	1.7211*	-1.1165	3.9518***	2.4926**	2.796**
$\tau(0,15)$	0.13266	2.6166**	-0.18606	4.2259***	1.3663	1.6877*
$\tau(0,20)$	0.54101	2.2142**	0.4535	3.9241***	3.3274***	2.768***
$\tau(0,25)$	1.1153	3.1247***	1.1503	4.4871***	6.0494***	3.8513***
$\tau(0,30)$	1.2408	3.1244***	1.119	4.1511***	5.7337***	3.6914***
$\tau(0,35)$	1.2971	3.1319***	1.3856	3.8401***	3.5538***	3.6733***
$\tau(0,40)$	1.4605	3.4092***	1.7021*	4.2461***	4.388***	4.4361***

Quite remarkably, the market model with the PFTS index seems to do very well during the growth period. Although longer event windows do worse than shorter ones (significance already appears on day 43), practically no reaction is seen up to day 20. It is easy to conclude from the table that the *MMp* methodology should be used for data up to day 1108. Noteworthy is the fact that the sign test, which is supposed to provide robustness to the Market Model result actually does worse than the measure itself and should therefore be ignored.

Table 5 Market reaction during the deterioration phase (post 15/01/08) by methodology to randomly generated fictitious events

	<i>MMp</i>	<i>MMpST</i>	<i>MAR</i>	<i>MARST</i>	<i>MMeq</i>	<i>MMSTeq</i>
$\tau(0,1)$	-0.65929	0.2889	-1.0981	-1.5315	1.5151	-0.55773
$\tau(0,2)$	-0.55659	-1.0278	-1.6303	-2.4286	1.2955	-0.6702
$\tau(0,3)$	-3.0692***	-1.0287	-4.2497***	-2.8853***	1.2767	-0.5612
$\tau(0,4)$	-2.695***	-0.3995	-3.9906***	-3.4799***	3.0275***	-0.592
$\tau(0,5)$	-2.2964**	0.45736	-4.0067***	-3.2666***	2.1172**	-0.48907
$\tau(0,7)$	-4.2711***	-0.42429	-6.1235***	-3.8289***	-0.078128	-1.3803
$\tau(0,10)$	-4.8499***	-0.64646	-7.5063***	-4.7673***	0.93503	-1.4036
$\tau(0,15)$	-5.3135***	-1.7224*	-8.2617***	-6.2456***	2.2335**	-2.1769**
$\tau(0,20)$	-6.6198***	-3.6439***	-10.147***	-7.4591***	3.0465***	-1.9853**
$\tau(0,25)$	-7.921***	-4.6434***	-12.403***	-8.9686***	2.1375**	-1.6143
$\tau(0,30)$	-8.6208***	-4.2557***	-13.28***	-8.2655***	3.2144***	-1.6662*
$\tau(0,35)$	-7.7588***	-3.6801***	-13.39***	-8.6889***	1.7393*	-1.3144
$\tau(0,40)$	-7.8574***	-3.0548***	-13.971***	-8.7147***	0.8384	-1.5299

As expected, the deterioration period seems to be practically unusable for analysis, as all measures fail to provide even reasonable results. It seems that this research has arrived at a dataset for which conventional event-study analysis simply breaks down. It should also be remarked however, that even though the *MMeq* methodology still performs rather poorly, it does so better than the traditional *MMp*.

Measuring the Market Reaction

As concluded from the previous section, to measure the market reaction to different recommendations it is best to only use data up to 1108²⁰ days and the Market Model with the PFTS index. Event periods are also best kept up to 20 days in length. Given such stringent measures, the strong-buys are no longer possible to estimate, which is already a big conclusion. Reporting any sort of

²⁰ This converts to 742 trading days

statistics on the strong-buys would most likely give a false impression of what is really going in the market. The market reaction to buy, hold, and sell recommendations, however, are provided in tables 6 and 7. This time all results include event-clustering corrections and the number of observations for the first and last event windows are provided in brackets next to the recommendation name²¹. It should also be noted that the \overline{CAR} and \overline{AR} estimates are computed separately with the largest number of observations permitted for each calculation²².

²¹ For example for buy recommendations the numbers in the brackets should be read as follows: 203 observations were used for the (0,1) \overline{CAR} computation and 176 observations were used for the (0,20) \overline{CAR} computation

²² This means that \overline{AR} measures will not always add up to \overline{CAR} measures exactly, as each is the best estimate in its own right and is based on a potentially different number of observations

Table 6 \overline{CAR} and \overline{AR} with τ -statistics for buy and hold recommendations prior to 15/01/08

	Buy (203, 176)				Hold (113, 91)			
	\overline{CAR}	τ	\overline{AR}	τ	\overline{CAR}	τ	\overline{AR}	τ
(0,0)	--	--	0.0008339	0.3919	--	--	0.0028842	0.82292
(0,1)	0.014703	2.9365***	0.013687	3.7103***	-0.0076763	-1.1487	-0.010575	-2.4478**
(0,2)	0.018632	3.0710***	0.0039292	1.1662	-0.0091713	-1.1747	-0.001495	-0.41027
(0,3)	0.017622	4.2179***	-0.0010929	3.1097***	-0.028451	-3.6504***	-0.019249	-5.2701***
(0,4)	0.018834	4.5425***	0.0012126	1.7216**	-0.030651	-3.6762***	-0.001387	-0.78079
(0,5)	0.0205	4.2954***	0.0032338	0.7851	-0.034317	-3.7371***	-0.0028555	-0.80242
(0,6)	0.024087	4.2724***	0.0029743	0.69308	-0.030536	-2.9443***	0.0028292	0.99169
(0,8)	0.018448	3.4514***	-0.006658	-1.249***	-0.023131	-2.1353**	5.944e-006	-0.236
(0,10)	0.015967	3.4712***	0.0026383	1.9494*	-0.021152	-1.6426	0.0028977	1.1211
(0,12)	0.013125	2.5316***	0.0024894	-0.092165	-0.032979	-2.4734**	-0.011259	-2.6061**
(0,14)	0.0029404	1.6123*	-0.0037403	-0.72229	-0.031818	-2.2653**	0.0008867	0.077556
(0,16)	0.010556	2.5082***	0.0031334	1.6238	-0.017151	-1.5838	-0.0069942	-1.9107*
(0,18)	0.0061568	1.8628**	0.0026896	0.87136	-0.023412	-1.8985	-0.0077773	-2.6683**
(0,20)	0.0081335	1.6143*	-0.0007275	-1.3247	-0.01399	-1.7137	0.0041134	-0.15773

The table on the previous page suggests that the market does react in a significant manner to buy recommendations, at least over the first 20 days. While the average abnormal return does seem to go up and down, its positive corrections are on the whole much more significant than negative ones. The largest positive daily abnormal returns are found for days 1, 4, and 10, reaching a level of over +1.4% on day 1. The cumulative average abnormal returns are significant and positive for all time-bands up to 20 days in length. Longer event periods seem to be going down in significance as compared to shorter ones, suggesting that the positive market reaction is diminishing over time. On the whole it seems that the peak reaction is found at 6 days following publication, reaching an overall cumulative +2.4% in abnormal returns.

Hold recommendations seem to induce exclusively negative abnormal returns, which reach peak significance over time-bands of 3 through 14 days in length²³. The \overline{CAR} statistics for the (0,5) event period reaches a -3.4% in cumulative abnormal returns, which is roughly 40% larger in magnitude than the biggest reaction to buy recommendations. While the reaction to holds seems to diminish with time even more rapidly than the reaction to buys, the market's response in this case also seems to take longer to develop. Daily average abnormal returns seem to interchange between being positive and negative, although qualitatively negative ones occur more often. The largest of these occurs on day 3 and reaches -1.9%, which is only 0.5% smaller in magnitude than the largest positive return found in the market reaction to buy recommendations.

²³ The reaction for a 10-day long time-band seems to be negative but insignificant. It does not really suggest a break in the trend, however.

Table 7 \overline{CAR} and \overline{AR} with τ -statistics for sell recommendations prior to 15/01/08

Sell (101, 81)				
	\overline{CAR}	τ	\overline{AR}	τ
(0,0)	-0.0061153	-0.41057	-0.0061153	-0.41057
(0,1)	-0.010337	7.5383	-0.0042326	11.067
(0,2)	0.0038474	8.9473	0.014185	4.8364
(0,3)	0.0084437	8.1729	0.0030968	0.4163
(0,4)	0.013065	8.1331	0.0046213	1.8404
(0,5)	0.020744	8.18	0.0073808	1.6194
(0,6)	0.031578	19.342	0.010417	30.959
(0,8)	0.037479	18.945	0.0034908	-0.45775
(0,10)	0.027863	4.4433	0.00050146	1.4376
(0,12)	0.046885	4.7569	0.014541	3.0169
(0,14)	0.050012	5.918	0.0037412	-0.28556
(0,16)	0.043621	5.4684	0.00097212	0.44388
(0,18)	0.042679	4.7837	-0.0038766	-0.44337
(0,20)	0.047219	4.7679	0.0065912	2.2892

The strangest result of all is actually found for sell recommendations. While being insignificant in producing negative abnormal returns, the sell recommendations in fact turn out to produce very positive market reactions! In fact the \overline{CAR} value for the 12-day time-band is +5.0%, which is over two times greater in magnitude than the largest reaction seen for the buys. The \overline{AR} measures also tend to be large and positive, reaching an unbelievable +1.5% on days 2 and 12. While these results may seem rather surprising it should be kept in mind that the provided measurements are not primary but secondary market reactions. A possible explanation for such findings is that the market negatively overreacts during primary dissemination and then corrects itself afterwards, which shows up as a positive reaction.

On the whole the results suggest that the market either reacts to secondary disseminations or corrects itself after primary ones. Whatever the reason, it can be concluded that the PFIS seems to be rather inefficient.

Reputational Effects

The results of the previous section suggest that the Ukrainian stock market is likely to suffer from inefficiencies, as it reacts significantly to “old” information. One possible intuitive explanation for such findings is reputation. While there may be little value to analytical recommendations which have already been previously announced, traders may still respond to publications if they are issued by trustworthy companies. An alternative explanation would be that traders react to recommendations they find in Bloomberg made by brokerage houses they believe the public or other traders to trust. One way to observe whether reputation plays a role in formation of abnormal returns is to filter recommendations by brokerage house and see whether publications issued by certain houses create greater abnormal returns than by other ones. Because many events have to be excluded from estimation due to event clustering, only the largest companies can be tested²⁴. Table 8 presents τ -statistics of \overline{CAR} responses to buy recommendations²⁵ issued by different houses.

Table 8 τ -statistics of \overline{CAR} s by brokerage house prior to 10/01/08

	<i>Concorde</i>	<i>Dragon</i>	<i>RenCap</i>	<i>Troika</i>
$\tau(0,1)$	2.8753***	-0.1946	1.0107	2.2774**
$\tau(0,2)$	2.1553**	-0.18142	2.1501**	1.8195**
$\tau(0,3)$	3.5201***	0.16225	2.3023**	1.2615
$\tau(0,4)$	4.9627***	-0.073271	1.8325**	1.9818**
$\tau(0,5)$	4.7229***	-0.60222	1.1471	1.5011*
$\tau(0,7)$	4.6201***	-0.013107	1.5362	1.6716**
$\tau(0,8)$	4.6386***	-0.37161	1.1723*	1.6573*
$\tau(0,9)$	4.247***	-0.39131	0.40373	1.7204**
$\tau(0,10)$	4.4878***	-0.59753	0.62457	1.6092*

²⁴ For these estimates event periods with mixed recommendations types are left in the estimation, as otherwise the number of observations becomes too small (the number of observations for all estimates becomes greater or equal to 60).

²⁵ Only responses to buy recommendations are provided, the reaction to buys is overall the cleanest one

The results suggest that a reputational may indeed play a significant role in formation of abnormal returns. Companies such as Dragon Capital, which are likely to be distrusted by traders, create absolutely no market reaction when publishing their buy recommendation on Bloomberg. Concorde Capital's recommendations, however, seem to produce very significant positive abnormal returns. Troika Capital and, to a lesser extent, Renaissance Capital also seem to also produce abnormal returns, but their significance is roughly half that of Concorde.

Alternative explanations for such discrepancies may lie in the amount of time that passes between original and secondary dissemination for different companies and the client base of each particular company upon primary dissemination. If it were the case that Dragon Capital took longer to publish on Bloomberg and had a very large client base when compared to Concorde Capital, one could expect that the reaction to the latter company's secondary publications would seem larger, as the market would not be able to absorb as the information as easily. While it cannot be stated with certainty that Concorde and Dragon take the same amount of time to publish their recommendations in the database, there is no real reason for the timings to differ substantially. Furthermore, since publications later in time benefit each of the company's direct clients, it is likely that the brokerage houses would compete and therefore publish approximately with the same time lag, as otherwise they would be at risk of losing clients to their competitors. The client base for each company can be judged approximately by the number of recommendations made since the beginning of its existence, as companies with larger client bases typically have more analysts and thus provide a larger scope of analysis. The total number of recommendations made by Concorde Capital is 412, which is marginally higher than Dragon Capital's 384. Such findings suggest that Dragon Capital is unlikely to have a larger client base.

CONCLUSIONS

Overall, three important points can be concluded from this research. First, conventional abnormal return measures have very low robustness properties and may fail when faced with unconventional stock patterns. Although according to the fictitious random event simulation the Market Model with the PFTS index provided the most reliable results, the generalized sign test for this procedure fails almost completely. Ironically, the nonparametric tests are the ones that are supposed to provide robustness in event studies. Second, the Ukrainian stock market displays signs of inefficiency when tested against the H_0 of no reaction to secondary dissemination, yielding as much as +2.4%, -1.9%, and +5.0% of cumulative abnormal returns to buy, hold, and sell recommendations respectively. It can thus be concluded that semi-strong and strong-form inefficiency is observed. Finally, it can also be concluded that reputational effects are likely to play a role in formation of abnormal returns. This is indicated by high significance of abnormal returns created by buy recommendations of some firms and no significance created by others.

Perhaps the strangest result this work has arrived at is the positive market reaction that appears to occur in response to Bloomberg publications of sell recommendations. It can be concluded almost for certain that traders pay practically no attention to sells, as stock prices show no sign of deterioration after such publications. One possible explanation for positive abnormal returns is that the market corrects for overreactions which occur times of primary dissemination.

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