Capital Market Efficiency in Poland:

An analysis of weak form efficiency on the Warsaw Stock Exchange

A Honors Thesis for the Economics Department

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I. Introduction

This study examines the Warsaw Stock Exchange (WSE), an emerging stock market thirteen years into its development. The WSE was the second of the Eastern European Capital Markets to open after the fall of Communist economic control in Eastern Europe. The creation of an open and free securities market is important to these transitioning economies, as a mechanism to accurately represent the capital/investor relationship. A securities market is an information mechanism that better allows the market economy to efficiently allocate capital. However, the efficient operation of the security market itself is critical to this development. Likewise, the securities market could provide an important facility for the privatization of old industries, as well as a source of capital for new ideas and firms. In all these respects, a free capital market is important to economies, such as Poland, in their development and transition from planned economies. Therefore, deciphering its efficiency is an important topic that serves investors, firms, and society as a whole.

This study was performed with the intention of answering four relevant questions on financial market efficiency in Poland. First of all, does the WSE serve as an efficient and accurate information collecting mechanism for the Polish capital market? It is important to both private and government members to be able to rely on data from the financial market as a reliable measure of the market for capital. This question focuses on the WSE's role of representing the allocation of capital resources, and whether this process is carried out efficiently. Though the results show significant improvement when compared to other emerging markets, the in-depth stock analysis shows significant inefficiencies.

Though the existence of market inefficiencies often requires the ability to make systematic profit, this is not necessarily true on the WSE, which blocks trades after a security has changed by 10% in one day. Therefore, the ability to make a systematic profit is a separate question that needs an extension of the standard results to answer. Tests, which discounted for this regulation, still found stocks to be weak form inefficient today. Therefore, informed investors can outperform the market return by seeking out profitable trading strategies. Though the suggested trading strategies are significant, the discovery proves the existence of profitable strategies and encourages the search for others.

The third question inspiring the tests in this study asks how the WSE compares to other emerging markets of similar age. The WSE is shown to be in the higher tier of efficiency of the other emerging markets for which data is available. The other available research on emerging market efficiency only analyzes all-share market indices, representing all the securities on an exchange. This is done mainly because better data does not exist for these other exchanges. Effects, which might create inefficiency in individual securities, are averaged out on the index as a whole. Therefore, these results provide some insight into how the markets compare, but are not at all precise.

Lastly, this research considers what lessons can be learned from the development of the WSE for other emerging security markets. Though certain trends are visible in the results, the most significant is the rapid advance in market efficiency that was observed with the introduction of the WARSET electronic trading system, a modern system used in numerous developed markets. The readily available access to the market provided by this system, and full information returned to investors was shown to be very significant in improving the WSE in term of efficiency and advancing it past other similar exchanges. The otherwise slow incorporation of improved information can assist other financial market participants with their expectations. These lessons are also likely to pertain most to the WSE itself, which still has much development in its future.

II. Literature Review

The subject of market efficiency has been intensely studied over the last 30 years. (Fama 1991) The main principles of market efficiency were consolidated in 1970 by Eugene Fama in his “Efficient Capital Markets: A Review of Theory and Empirical Work,” which is a review of the most important efficient market literature available at the time. In doing so, Fama lays down the theoretical framework upon which market efficiency research is based. Fama likens market efficiency with the ability of firms to make effective “production-investment decisions” based on financial market prices. This idea is the core of what is today known as the Efficient Market Hypothesis (EMH). The EMH implies that systematic profit in capital markets is impossible, and is this way tested. However, Fama goes beyond defining market efficiency and divides the research on the subject into three groups or degrees of efficient markets: weak form, semi-strong form, and strong form.

Weak form market efficiency is the lowest form of efficiency, and only requires that past prices and returns cannot be used as a predictive tool for future security returns. Weak form efficiency can be tested by the fair game and random walk models described in the Fama literature. He shows developed financial market to be weak-form efficient even in 1970. The recent literature is, on the most part, simple extensions of the Fama studies. Magnus Magnusson and Bruce Wydick discuss weak form efficiency in the new African markets and cite similar tests for South Asian and Latin American markets. This paper summarizes the state of emerging markets around the world from a weak form efficiency perspective. However, their results are mixed; only five of the eight African markets focused on are found to conform to a standard random walk model. My study draws heavily from the theoretical framework laid down in Fama and application from these newer works, such as the Magnusson and Wydick study.

The collection of literature concerning financial market efficiency specifically of Poland's WSE is, by all means, limited. However, basic tests of market efficiency have been performed. The paper by Fred Wheeler, Bill Neale, Thadeusz Kowalski, and Steve Letza studies the Warsaw Stock Exchange between 1991 and 1997 in an attempt to discern weak-form efficiency. The paper finds the earliest securities trading on the exchange to exhibit significant serial correlation. An important barrier to efficiency was found to be a trading regulation, which does not allow securities to trade outside of a 10% range on any given day. The methods used in this paper will be extended to the entire set of securities trading up to today.

Harald Henke approached market efficiency from a different angle by focusing on the January effect. The January effect is usually explained to be a result of tax benefits to selling stock at the end of the year. (Jones, Pearce, and Wilson 1987, p453). However, Henke suggests that this is not the case in Poland, since Poland does not have a security tax law. My research will extend his across other market segments. Though he makes an interesting discovery, his explanation might be lacking. Though Poland does not have a capital tax, foreign investors would still be subject to the tax laws in the country which they live in. Therefore, the January effect observed on the WSE might not be as peculiar, as Henke suggests.

While testing weak form market efficiency only requires historical price data, the semi-strong and strong form efficiency tests introduced in Fama's 1970 work are more complicated because they require some form of fundamental data. Though these results would be very relevant, the analysis is not possible with the limited fundamental data available from the WSE.

III. Theory of Weak Form Market Efficiency and Applications

Market efficiency theory is rooted on the principal that markets should effectively allocate owner resources among capital stock. (Fama 1970)

> "In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time "fully reflect" all available information. A market in which prices always "fully reflect" available information is called "efficient" (Fama 1970, p383).

This is an important aspect of the Efficient Market Hypothesis (EMH), which was introduced by Fama shortly before his survey on the literature. The EMH requires that outperforming the market consistently is impossible. Prices should equal the discounted value of future cash flows (Brealey and Myers 2003, p346- 347). In an efficient market, currently available information is used to make a best estimate of future cash flows or dividends. These future cash flows are then discounted to represent the individual's preference for returns closest to the present period. According to this theory, future returns are based on random information not available in the current environment.

The EMH is important to studies of market efficiency because it implies that systematic profits in financial markets are impossible. To systematically make a profit in a capital market the investor must possess some sort of superior knowledge or method. This could mean a trading strategy based on publicly available information, which can consistently be implemented to make a profit, or better information with which to make decisions that all market participants do not have available. A market conforming to the EMH rules out both of these possibilities because they would allow for systematic profit. If the EMH can be proven to hold for a certain market, investors can not consistently “beat the market.” (However, investor returns still experience risk and variability that can be mistaken for outperforming the market in the short-run.) In such a market, investors can not expect returns higher than the market return and therefore should not waste time and money attempting to do so. Therefore, testing for the EMH is very important to investors since it gives insight into the optimal investment strategy.

Fama set the standard by dividing the work and study of market efficiency into the three subcategories of weak, semi-strong, and strong form efficient market hypothesis. These levels define degrees of efficiency and require variations in technique to study. They are discussed further here with an emphasis on the weak form efficiency, which is applied in this study.

1. Fair Game Model

Weak form market efficiency is the lowest form of efficiency. It requires that past prices and returns cannot be used as a predictive tool for future moves in asset prices. (The equations used here to describe the models come from the Mandilaras class notes, as their meaning is identical to the Fama literature.) Weak form efficiency can be tested by the general group of fair game models. The fair game model assumes there is no systematic difference between actual and expected returns (Mandilaras 2003). This is tested by creating the following model:

$$r_{i,t+1}=E(r_{i,t+1}|\Omega_t)+\epsilon_{i,t+1} \qquad \text{Eq. 1}$$

where at time t+1 $r_{i,t+1}$ is the actual return to security i, $E(r_{i,t+1}|\Omega_t)$ is the expected return conditioned on the set of information available at time t, and $\epsilon_{i,t+1}$ is the set of residuals. A fair game is described by characteristics of the residual terms. The error term must have three properties. First, it must have a condition expected value or conditioned average of zero:

$$E(\epsilon_{i,t+1}|\Omega_t)=0 \qquad \text{Eq. 2}$$

Therefore, actual return does not differ systematically from the expected return. This implies that expected returns are rational. Furthermore, the error term must be uncorrelated with the conditional expected return.

$$E(\epsilon_{i,t+1}E(r_{i,t+1}|\Omega_t)|\Omega_t)=E(r_{i,t+1}|\Omega_t)E(\epsilon_{i,t+1}|\Omega_t)=0 \qquad \text{Eq. 3}$$

This means the error term must be conditionally independent of the magnitude of the conditional expected return on the investment. Lastly, the error term must not be serially correlated.

$$E(\epsilon_{i,t+1}\epsilon_{j,t+1}|\Omega_t)=0$$

Eq. 4

$$E(\epsilon_{i,t+1}\epsilon_{i,t}|\Omega_t)=0 \qquad \text{Eq. 5}$$

$$E(\epsilon_{i,t}\epsilon_{j,t+1}|\Omega_t)=0 \qquad \text{Eq. 6}$$

These properties of the residual term define a fair game, and all must hold for a fair game to exist. These are testable models of weak form market efficiency that focus on the relationship between conditional expected and actual return. Likewise, data for both of these variables is necessary to test a fair game model.

A very similar model is the sub martingale model, which only makes one small adjustment to the above. In the sub martingale model, the expected return is considered to be slightly positive instead of zero (Fama 1970, p386). This adjusts for empirical results, which show that the returns on investments are positive. This is caused by the risk inherent to capital investment. The resulting change to equation 2 is:

$$E(r_{i,t+1}|\Omega_t) \geq 0. \qquad \text{Eq. 7}$$

2. Random Walk Model

Theory

A separate extension of the fair game is the random walk model. While the fair game model essentially only requires the error term to have a conditional mean of 0, the random walk model requires the residuals to also be distributed normally. Since changes in fundamental values and prices are based on news, the following must hold:

$$E(r_{i,t+1}|\Omega_t)=r_{i,t}. \qquad \text{Eq. 8}$$

The expected return tomorrow is simply the return today. One can then transform Eq. 1 to:

$$r_{i,t+1}=r_{i,t}+\epsilon_{i,t+1}. \qquad \text{Eq. 9}$$

The best estimate of tomorrow's return is today's plus an error term. Tests of this model require studying the residual terms, as in the fair game model. Since the model is derivative of the fair-game model the same restrictions must be placed on the error term for it to hold (eqs. 2-6). A random walk extends the fair-game model to include formation of expectations. The model requires that security prices fully reflect all available information concerning the security, and returns to be evenly distributed and independent of previous returns (Fama 1970, p386-387). In practice, this requires the residual term to have an actual mean of zero,and not just a conditional mean of zero.

Application

Empirically, weak form market efficiency has been shown to exist in US and UK financial markets (Fama 1970). The studies entail looking for significant serial correlation in market returns. However, these early studies were not entirely conclusive. Weak-form efficiency research also involved tests of specific trading strategies and their effectiveness. These were shown to be generally ineffective. Bachelier proposed testing security returns' likeness to a normal distribution, as in the random walk model. The empirical results of the time show returns closely matching a normal distribution with the exception of "high tails." This implies high standard deviation moves are disproportionally likely. However, Fama concludes that these distributions are stable and do not contradict the random walk model because returns are still evenly distributed though a higher amount of volatility is observed than is expected by the normal distribution (Fama 1970).

Most of the tests from the recent literature are simple extensions or derivatives of earlier ones. These results have been mixed. Papers, such as Magnusson and Wydick's, seem to prove weak from efficiency exists in a number of the new African markets and cite similar results for South Asian and Latin American markets. Though weak form market efficiency is further broken down into 3 degrees in this study, five of the eight markets studied are found to conform to a basic random walk model. A simpler study is conducted on the Gulf countries by Mohamed El-Erian and Manmohan Kumar. The study discovers some evidence of weak-form inefficient markets. Serial correlation of higher degrees is found in the study of market indices, which indicates that price movements can be predicted by previous returns. This study is implemented firstly by testing for autocorrelation in the residuals of a random walk model. The El-Erian and Kumar study also implements a runs test, which has a similar objective to the autocorrelation test. However, the runs test is non-parametric and does not depend on the magnitude of price changes. Equal studies will be implemented on WSE index and individual stock data in this paper. These results can then be easily compared to these previous studies.[1] However, the previous studies of emerging markets are very much constricted by the available data, and only provide the general results summarized above. Therefore, the comparison of markets will be at a most

[1]For more details see the Methodology section of this paper, Chapter 6.

superficial level, since only these weak-form efficiency test results can be compared.

IV. Historical and Financial Background of Poland

1. The Warsaw Stock Exchange

The Warsaw Exchange has a surprisingly long history dating back to 1817, when an equity and debt exchange was opened in Poland. This exchange grew over the next hundred twenty years and actually had 130 instruments trading in 1938, right before the beginning of World War II (Warsaw Stock Exchange, "About the Exchange:History"). However, with the acceptance of the Communist economic and political system came the abolishment of free-markets, including the Warsaw bourse. After the fall of communism in eastern Europe, the Warsaw Stock Exchange was resurrected in 1991. The Warsaw Stock Exchange joint stock company was created by the State Treasury as a significant step in liberalizing the economy and capital markets. On April 16, 1991 the exchange opened its doors, though only 5 securities traded at the time. Since then, the exchange has made significant progress and now operates a viable trading system with similar characteristics and controls as other developed financial markets. The exchange has attracted a significant amount of foreign investment, which represents 35% of shareholders in the last survey. (See Table 1.) However, the number of institutional investors is relatively small in comparison to developed markets (Henke 2004). Furthermore, the WSE has experienced significant growth in terms of market capitalization and market turnover, seen in Table 2. In theory, efficiency should improve as the exchange and trading volume grows (El-Erian and Kumar 1995).Though this claim maintains some truth on the WSE, it is far from a complete picture of the changes occurring on the exchange.

Table 1. WSE Trading by Investor Type

Investors	Instrument	1997	1998	1999	2000	2001	2002.1	2002.2	2003.1
Foreign	shares	38	39	34	28	34	36	34	35
	Futures	-	-	4	2	2	1	2	2
Domestic Individual	shares	38	39	44	50	37	31	27	28
	Futures	-	-	81	85	83	80	79	75
Domestic Institutional	shares	24	22	22	22	29	33	39	37
	Futures	-	-	15	13	15	19	19	23

Source: Warsaw Stock Exchange Website
Note: The table is from a survey of market participants, showing what percentage would qualify themselves as foreign investors, institutional, or individual investors. The survey was conducted between 1997 and 2003.

Table 2

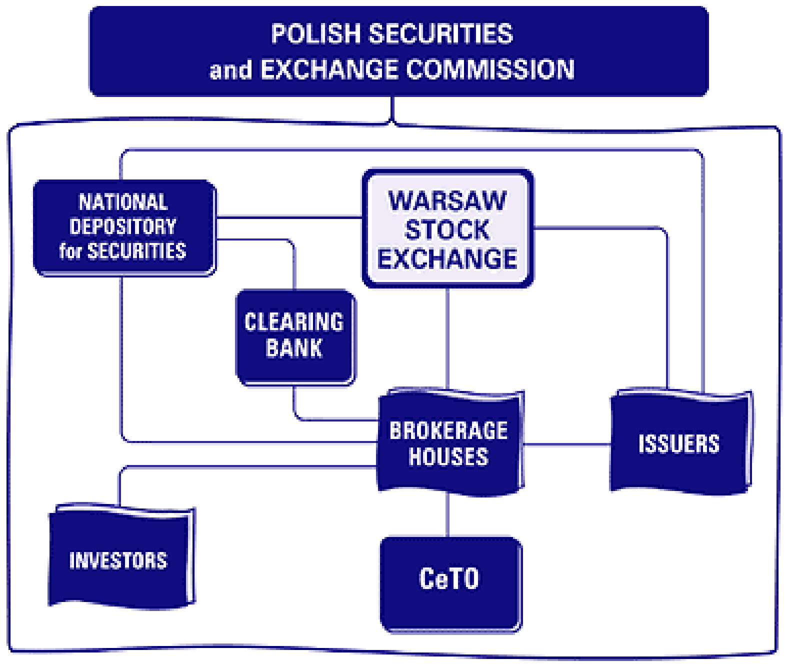
(This will be visible in the attached file.)

The table shows the most important statistics for the WSE, and their growth.

2. Polish Capital Structure

The structure of the Polish Capital markets is very similar to that of the US. (See Graph 1.) The Polish Securities and Exchange Commission overlooks and monitors all aspects of the system to maintain fair and balanced transactions. This is an important feature to any investor that provides some assurance that his/her capital won't be mishandled. At the heart of the actual system is the Warsaw Stock Exchange. Companies can issue their shares as long at the book value of the company exceeds four million PLN, the value of the shares exceeds four million PLN, and the Exchange Supervisory Board approves the listing (Warsaw Stock Exchange website, “About the Exchange: Regulations”). Issuers use the services of brokerage houses to list and offer equity or debt instruments on the exchange. Likewise, investors can access the exchange by having an account with a brokerage house. These brokerage houses can also access CeTO (Central Table of Offers,) Poland's over the counter exchange. These instruments do not have to meet the WSE's requirements for listing or maintenance, but are subject to the Polish Security and Exchange Commission's rules and scrutiny. This electronic trading system is intended for smaller firms to raise capital and awareness. The National Depository for Securities provides clearing and settlement services for all publicly traded securities (Warsaw Stock Exchange website, “About the Exchange”). These components make- up the Polish capital market. This model, very similar to that in the US, will allow the capital markets to operate effectively and grow if the established guidelines and rules are effectively enforced.

Graph 1. Polish Capital Structure



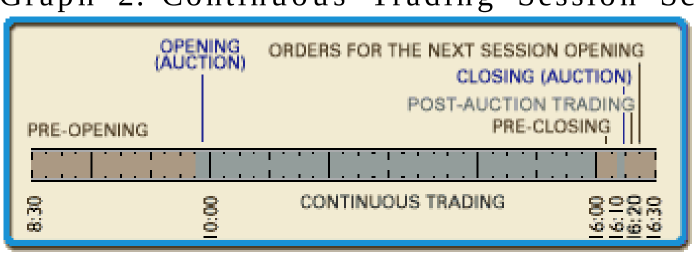
Source: Warsaw Stock Exchange Website
Note: This graph represent the structure of the Polish Capital market and the important groups within it. The lines show links and contact between groups.

The trading system in place since November 17, 2000 is the Warsaw Stock Exchange Trading System, know as the WARSET. Virtually identical systems are in place in Paris, Brussels, and Amsterdam. The electronic system automates order handling by directly forwarding customer orders from the brokerage house to the exchange. The system then matches orders based on the following objectives: a) maximizing volume , b) minimizing the size of sell and buy orders at the trade price, c)minimizing the trade price and theoretical price (specifically on opening trades). These principles hold in matching trades throughout the day, but are most important in determining the opening price when the order book can be full of orders, and an opening price must be determined to maintain the above principles (Warsaw Stock Exchange website: “About the Exchange”).

Trading on the WSE is either continuous or in a single-price auction. Continuous trading is prevalent today in the most liquid stocks and all bonds, investment certificates, futures, and warrants. Continuous trading begins between 9:00 and 10:00 AM, depending on the type of security, and closes at 4:10 PM. (See Graph 2.) The opening and closing of the trading day is done by auction, where all the orders in the book are matched to determine one price and all orders at or better than this price are cleared. The same procedure is used on many other exchanges around the world. During the day, orders are matched as they come in.

Securities trading on the single price auction system often trade in much lower volume. They trade in two auctions daily at 11:15 AM and 3:00 PM, which are held on the same principles at the opening and closing auctions for continuous trading. Investors can also trade on the auction price for 30 minutes after the auction. The WARSET also supplies traders and brokers with full real-time information on the order book and trading in all securities.

Graph 2: Continuous Trading Session Schedule



Source: Warsaw Stock Exchange Website
Note: This represents the daily schedule of the WSE.

This system seems to be an efficient electronic trading system used in numerous places around the world that provides vital information to participants. Since order matching is performed electronically, there is little room for trade tampering. An earlier study of WSE efficiency done by Wheeler, Neale, et al. implied that trade prices are somewhat contrived, especially in the first couple years of trading. At this time, trading was not continuous and order matching was the responsibility of a broker. However, today's electronic trading system and continuous trading for liquid securities seems to circumvent these earlier problems. Furthermore, information seems to be improved since real-time and more detailed order information is available to brokers, and likewise investors.

However, one of the criticisms of the Wheeler, Neale, et al. paper that has not been resolved in the tight trading range regulation. Stocks can only move ten percent per day, based on the closing price of the previous day. Trading outside of this range is blocked. These price variation limits seem to disrupt efficient market transactions, as was found to be true in Wheeler, Neale, et al. The New York Stock Exchange (NYSE) uses limits on index movements not on individual stocks, as it is not extremely uncommon for NYSE issues to move outside of the 10% range. The price limits of indices might be necessary to protect a capital system if investors become irrational in the short term. However, protecting individual company issues like the WSE, will certainly be detrimental to market efficiency.

3. Indices

In my test, I look at several of the most important indices on the WSE. The WIG index is meant to best represent the total return of the WSE. It has 98 members and can be best compared to the S&P 500 index in the US. It is capitalization weighted, and no one stock can exceed ten percent of the value within the WIG. It includes dividends and preemptive rights and is reweighed on a quarterly basis. In general, it provides the best estimation of total market return, since it is the largest index.

In contrast, the WIG20 represents roughly the 20 highest turnover stocks trading on the WSE, though each of the major sectors must be represented. Each individual stock is assigned a rank based largely upon exchange volume. The stock's weight within the index is based on this ranking. However, dividends and preemptive rights are excluded from index calculations. The WIG20 is largely followed as a strong indicator of the WSE. Futures and option derivatives trade on the WSE, as well. It is very similar to the NYSE's Dow Jones Industrial Average in structure. Likewise, it is a popular and closely followed measure of market performance.

The MIDWIG is composed of 40 middle size companies not included in the WIG20. Like the WIG20 the index excludes dividends and pre-emptive rights, and uses a similar ranking system for weightings within the index. Lastly, the WIRR is a small cap index with 67 constituents currently. It is a total return index that requires constituents to have a positive book value, liquidity, and a value of less than 1% of total market capitalization.

For a full and more technical description of these indices, see Appendix A.

4. A Brief Political and Economic History of Poland since WWI

After the defeat of Germans and Austrians, Poland was given its independence in 1918. The 1919 Treaty of Versailles outlined the new Poland's boundaries and reaffirmed its independence. However, in 1920 Russia and Poland's dispute over eastern Poland led to a Russian incursion into the country. The Russians were eventually defeated at Warsaw and pushed back. In 1921, the newly independent and secure Poland created a republican constitution. However, republican Poland was short lived, as Pilsudski, a WWI military leader, effectively made himself dictator and dismissed Parliament. In the 1930's, Poland suffered economic depression and high unemployment. The dictatorship continued until 1939, when Nazi Germany attacked Poland and eventually succeeded. Though Poland spent most of WWII under German control, the USSR was awarded control of the country after the war.

The USSR gradually increased its influence of government in the region. In 1952, the new constitution modelled Poland after the USSR and simultaneously made Poland controlled by the USSR. In 1956, after the death of Stalin in 1953, Wladyslav Gemulka was able to rid Poland of some Soviet imposed policies. In December of 1970, Poland saw rapid inflation in food prices and riot broke out. Gemulka was ousted. Edward Gierek replaced him and attempted to improve living condition with varying success. However, recession again hit in the mid-1970's and the government had to again raise prices.

The sustained shortage and high price of food and housing led to the creation of the labor union Solidarity in the Baltic shipyards led by Lech Walesa, a shipyard worker. The labor union was given legal status for a short time and became very popular. Solidarity attempted to improve living conditions and reduce censorship. Despite this, marshal law was reinstated in 1982 and the group was banned. However, the union remained popular until the significant political reforms allowed free elections in 1989 (AllRefer.com, “Poland: The Communist Regime”).

In 1989, widespread liberalization took hold. Significant steps towards a free economy were taken. Lech Walesa was elected president in 1990. Walesa and Solidarity took radical steps to turn Poland into a market economy. The largest industries were reformed and privatized, prices were freed to market forces, and the currency was made convertible (AllRefer.com, “Poland:Solidarity and a Multiparty State”). The country soon fell to further economic difficulties in the early 1990's. The reforms resulted in hyper-inflation, good shortages, and high unemployment. Political instability was especially severe in this time, which included frequent shifts in power. However, by the mid 1990's, the economy improved and Poland became the best performer in Eastern Europe. Though Poland enjoyed economic success through the 1990's, the economy significantly slowed in 2001.

In general, the country of Poland has experienced poor living conditions throughout the last century. While the leaders hoped for a quick turnaround into a successful market economy, the people remained wary. The country's economy has been unable to pick up steam as quickly as the leaders had hoped, and the transition to a market economy has proved difficult. The people of Poland are still divided on the effectiveness of moving to a market economy, and a large group prefers the regulated system (Polish Ministry of Foreign Affairs website, “General information on the Polish economy”). This is an important aspect of Communist culture that is still present in Poland today, and its influence is still seen in aspects of the Polish economy.

V. Data

The data set used to conduct my research is made available by the Warsaw Stock Exchange (WSE). The Exchange has kept full records of transactions since trading was opened in 1991. The data tested in this research includes individual stock data from 1991, and includes all stocks as they were added to the WSE. This could be the auction prices if the equity is traded on a call-auction system or the final auction price from a continuous trading system. Though additional daily data was provided by the WSE, my analysis required only the closing prices from this data set. All the closing prices per year were delivered in yearly databases. To test efficiency factors across different years, the data had to be rearranged by stock and market segment, continuous or auction, across all the years in which it traded. After doing so, I was also better able to check for completeness and errors. In general, the dataset was complete. On several occasions the data was not in correct order in the delivered database. However, when the data was sorted, it did not leave any gaps.

The data did have some inconsistencies as to how no trade on a certain day was specified. This inconsistency was handled by the program used to test it. Any day that indicated a 0 for a price, replaced the 0 with the last available price, as was most common.

Furthermore, index closing data is important to my research and was obtained for the WIG, WIG20, WIRR, MIDWIG, and TECHWIG indices. The data delivered includes closing values since the introduction of each index. Like the individual stock data it was delivered on a per year basis, and had to be reorganized. In general, the data set seemed complete and correct after reorganization.

VI. Methodology

In this paper, I conduct a thorough analysis of the WSE to test for weak form efficiency. Most of my methods are derived from similar papers on emerging capital markets. Though this allows me to compare results, the form of the tests applied in other studies is rather narrow, focusing only on an all-share index representing the exchange. In most cases, I attempt to expand the tests across individual stocks and multiple market segments to obtain stronger results and to better answer the questions I set out to investigate.

1. Autocorrelation of Residuals

The autocorrelation test is the most significant and common test of random walk behavior. The autocorrelation test is a simple analysis of weak-form efficiency. For a certain security, price in period t (p_t) is equal to the previous day's price plus an error term,

$$p_{t+1} = p_t + e_{t+1}$$

The error term reflects the inclusion of any new information that becomes available in period t+1. If every period's market price fully includes all available information, the changes between periods should be independent of each other. Therefore, e_{t+1} should be independent of all previous e's and should not exhibit autocorrelation. (Wheeler, Neale, et al. 1997, p47-48) The test for autocorrelation of these residuals tests the null hypothesis that these residuals are independent of each other.

However, the price changes in a security do not follow a normal distribution. To get meaningful results from the residuals, one must look at the changes in price returns, which closely resemble a normal distribution. This is done by taking the natural log of the prices.

$$\pi_t = \ln(p_t)$$
$$\pi_{t+1} = \pi_t + \epsilon_{t+1}$$

The error terms should still be independent of all previous ones if the security i follows the EMH. The following hypotheses are set up to test the random walk theory, which requires these residuals to be insignificantly different from a standard normal distribution (Wheeler, Neale, et al. 1997, p 48).

$$H_0\text{:}\ \ ((\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-l}) \sim N[0, \sigma^2 I], \mathit{where}\, VAR(\varepsilon_t) = \sigma^2)$$
$$H_1\text{:}\ \ ((\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-l}) \sim N[0, \Omega])$$

Under the null hypothesis, a sample size of n has the following autocorrelation function:

$$r(k) = \frac{(\sum_{t=1}^{n-k} (\varepsilon_{t-k} - \bar{\varepsilon})(\varepsilon_t - \bar{\varepsilon}))}{(\sum^{n} (\varepsilon_t - \bar{\varepsilon})^2)} .$$

To test for autocorrelation in this function, I implement a Ljung and Box statistic, where n is the sample size and l is the number of lags being tested (Wheeler, Neale, et al. 1997, p48- 49).

$$Q = n(n+2) \sum_{k=1}^{l} \frac{(r(k)^2)}{(n-k)} .$$

This statistic is more powerful in deciphering small samples than the standard Box and Pierce statistic used for these tests, and is therefore implemented in my study (Gujarati 2003, 813). The Q statistic is compared to a chi- square distribution with l degrees of freedom to test if it is significantly different from 0. If Q is significantly different from 0, this means that autocorrelation is present in the sample. (Wheeler, Neale, et al. 1997, p 48) Such a result would allow us to reject the null hypothesis that price returns are independent.

This test was implemented by Wheeler to test for autocorrelation in the early history of the WSE. Their test created periods based on the number of trading days, and tested the same 16 stocks across the different periods. My autocorrelation test includes all stocks to trade on the main market segment of the WSE and four indices. This allows me to extend the results found in Wheeler and compare my index results to Magnusson and Wydick's study on African markets. The test across all market stocks expands the strength of the results, since stocks can be analyzed on an individual basis. I also introduce new period break downs for the time after 1995. My period break downs are based on historical events in an attempt to discover general trends in market efficiency over time. This type of testing also allows me to isolate certain factors as contributing to deterring from efficiency. The main events by which the period are broken down is shown in Table 3, and the 17 individual periods are shown in Table 4 (Periods 1- 17). [2]However, in testing the WIG20, I used a different period break down. This break down focuses more on the introduction of the WIG20 futures and any impact they might

[2]The number of test required to acquire these results would make a manual execution very time consuming. For this reason, all my tests on an individual stock basis were performed by a program which I made for this specific data set and for the specific tests I needed to perform. Copies of these programs can be made available on request.

have on the efficiency of the underlying index. These periods are 18- 24, as presented in Table 4.

Table 3. List of significant events used to break-up periods

Date	Significance
04/16/91	1 trading day per week begins
01/01/92	2 trading days per week begin
01/01/93	3 trading days per week begin
04/16/94	WIG20 quote begins
07/01/94	4 trading days per week begin
10/01/94	5 trading days per week begin
07/08/96	First 5 stocks introduced to continuous tradin
10/01/96	Real time data distribution introduced
02/03/97	WIG20 becomes continuously quoted
04/01/97	Reuters real time data introduced
01/16/98	WIG20 futures introduced
11/17/00	WARSET system introduced
11/26/01	MiniWIG20 futures introduced
01/01/03	Beginning of last year of full data
12/31/03	end of data

Note: This table represents the major information events for the WSE, which this study uses to break down periods. The events noted here are therefore tested for their significance.

Table 4. Description of Period Breakdowns

		PERIODS																							
Date	Description	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
04/16/91	1 td	X						X	X				X												
01/01/92	2 td		X					X	X				X												
01/01/93	3 td			X				X	X				X												
04/16/94	WIG20 intro.			X				X	X				X						X						X
07/01/94	4 td				X			X	X				X						X						X
10/01/94	5 td					X	X	X	X				X	X					X						X
07/08/96	Cont. trading						X		X	X			X	X					X						X
10/01/96	Real time data						X		X	X			X	X					X						X
02/03/97	WIG20 cont. quote						X		X	X			X		X					X					X
04/01/97	Reuters real data									X	X		X		X					X					X
01/16/98	WIG20 fut.									X	X		X			X					X	X			X
11/17/00	WARSET system											X	X			X						X	X		X
11/26/01	MiniWIG20 fut.											X	X				X						X	X	X
01/01/03	Last year											X	X				X	X					X	X	X
12/31/03	end of data																								

Note: This table presents each of the periods used throughout the analysis. Each of the periods begins on the date of the first x, and finish on the date after the last x.

2. Runs Test

The Runs test serves a similar purpose to the autocorrelation test, but is non- parametric in nature. Therefore, the magnitude of price change is inconsequential in this test. Like the autocorrelation test, it is commonly implemented in weak- from efficiency literature and provides a good basis for comparison. A run is defined as a sequential set of price changes of the same sign. To perform this test, I chose to use the model described in Gujarati (2003). The test compares the number of observed runs to the number of expected runs. In my test, observed run can include no change in price within the run. The number of expected runs is based on the total observations, number of positive changes, and number of negative changes. For this test,

N = total number of observations

N_1 = number of positive price changes

N_2 = number of negative price changes

R = number of observed runs

The null hypothesis says that successive outcomes are independent of one another, similar to the autocorrelation test. If $N_1 > 10$ and $N_2 > 10$, the number of runs is asymptotically normally distributed with the following mean and variance:

$$Mean = E(R) = \frac{(2N_1N_2)}{(N)} + 1$$

$$Variance = \sigma_R^2 = \frac{(2N_1N_2(2N_1N_2 - N))}{(N^2(N-1))}$$

I test for significance at the one, five, and ten percent levels. If the number of observed runs is within the range of mean runs plus or minus the Z-statistic times the standard deviation,

$$E(R) - (Z * \sigma_R) \leq R \leq E(R) + (Z * \sigma_R)$$

the null hypothesis cannot be reject. Otherwise, the number of runs, is significantly different than the number expected.

This test was performed on all the stocks and indices in my data set with the same period break down described above and visible in Table 4. The WIG20 index test was performed with the period breakdown shown in Table 4, periods 18-24.

3. Weak form Tests on Weekly Returns

While the above test looks at weak-form efficiency in daily prices, these results might not represent a practical profitable trading strategy. Since the WSE limits price moves in individual stocks by 10%, one would expect to observe weak- form efficiency. However, this might not be useful in developing a profitable trading strategy because no trading will occur if a security is valued outside of that 10% range. Therefore, to discount for the effect of this regulation, I conduct the same tests from above on weekly prices. Over a week's time, prices should be able to fully incorporate all information in most cases if the only preventing efficiency is the 10% regulation. Therefore, the tests above should result in not rejecting the null hypothesis if only the regulation prevents efficiency.

4. January Effect on the WSE

The January effect was first noticed in the US and says that stock returns in January outperform the monthly average consistently. Some studies also find that small stocks in particular perform best in January, as is noted in Jones, Pearce, and Wilson (1987). The traditional explanation for a January effect is that investors sell losing stocks at the end of the year to offset gain in other stocks, but then buy them back at the beginning of January. Another explanation says money managers sell losing stocks at the end of the year so they are not shown in the published annual report as holding certain losing stocks, which represent bad investments. However, these money managers then buy the losing stocks back in January. These are the main two explanations for the January effect.

Though the January effect seems to be absent in current US data, Harald Henke finds the January effect to exist in Poland (2003). Curiously, Poland has no tax benefit from selling losing stocks, and Henke conjectures that a window- dressing effect explains the January effect. Henke tests the WIG index for January effect for data between 1991 and 2002. I extend this test into 2003 and include the WIG20, MIDWIG, and other indices in my test described below. This will give me more up to date results on the January effect in Poland as well as an idea of its prevalence in larger or smaller stocks so I can make better conclusions about its existence on the WSE.

The first of the two alternative, but related models of the January effect in Poland is:

$$R_t = \beta_0 + \Sigma \beta_i M_{it} + \varepsilon_t$$

R_t represents stock returns in month t and M_{it} is a dummy variable with a value of 1 if the month is February though December and 0 otherwise. If no January effect is observed the null hypothesis that B_i are all zero should not be rejected. The existence of a January effect is supported if this null hypothesis can be rejected.

The second model is a result of the first and maintains that all B_i are equal.

$$R_t = \beta_0 + \beta_1 JAN_t + \varepsilon_t$$

$JAN_t = 1$ if the month is January and 0 otherwise. The null hypothesis of this model is that B_i is equal to zero. If B_i is significantly greater than zero, this is further evidence of a January effect in the security.

VII. Results

1. January Effect

The test of the January effect in this work mimics the work of Henke (2003). However, my data set is more up to date and my tests expand the research to include the WIRR, WIG20, and MIDWIG indices. This cross-sectional extension is important in drawing conclusions of the January effect across different market segments.

Table 5: Index Statistics: Average Returns and Significance

	WIG Mean	WIG Signif?	WIG20 Mean	WIG20 Signif?	WIRR Mean	WIRR Signif?	MIDWIG Mean	MIDWIG Signif?
JAN	0.070248	10%	0.060954		0.025847		0.035927	
FEB	0.035298		0.030004		0.063009	10%	0.003172	
MAR	-0.02231		-0.01524		0.017142		0.021446	
APR	0.04117		0.054856		0.057406		0.012621	
MAY	0.049682		-0.00381		-0.00327		-0.00942	
JUN	-0.04359		-0.04097		0.002042		-0.0049	
JUL	0.039331		0.009487		-0.01403		-0.00198	
AUG	0.025729		0.001792		-0.00013		-0.03537	
SEP	-0.03883		-0.05824	10%	-0.03383		-0.05807	
OCT	0.027823		-0.01522		0.003035		0.035197	10%
NOV	0.005131		-0.00045		0.008414		0.018952	
DEC	0.062805	5%	0.029754		0.039526	10%	0.061335	5%

Note: This table summarize the results for the four indices, which I tested for a January effect. The mean column for each index reports the mean return for each month over the last 13 years. The significance column implements a Student's t test to calculate significance of the mean's difference from 0.

The WIG results closely resemble the Henke observations. This is to be expected since this data only includes two more observation for a total of 13. Though none of the other indices exhibit a return significantly different from 0, all of the indices show positive January returns. Furthermore, the December mean returns are interesting to note, since they are all positive. The December return is also shown to be significant in the WIRR and MIDWIG returns at the 10% and 5% levels respectively. The positive and significant December returns seems to be the most clear common feature of the indices, and even the WIG20 December return has a t-statistic of 1.28, which is reasonably high. Though the returns in other months are not commonly significant, the positive January return are interesting and allude to the significance of a January effect under more rigorous evaluation.

The January effect test are expanded by testing the 2 regression equations introduced in the Methodology section of the paper. The results of these tests are reported in Table 6.

Table 6. Results of Monthly Regressions

	WIRR 1	WIRR 2	WIG20 1	WIG20 2	WIG 1	WIG 2	MIDWIG 1	MIDWIG 2
a0	0.0126	0.014	0.061	-0.0012	0.0736	0.0159	0.0362	0.004
	[0.679]	[0.124]	[0.089]	[0.908]	[0.055]	[0.161]	[0.236]	[0.680]
a1		-0.0013		0.0622		0.0577		0.0323
		[0.966]		[0.094]		[0.142]		[0.312]
a2	0.0532		-0.031		-0.0413		-0.0372	
	[0.207]		[0.539]		[0.443]		[0.388]	
a3	0.0215		-0.0762		-0.0933		-0.0125	
	[0.608]		[0.133]		[0.084]		[0.771]	
a4	0.0301		-0.0061		-0.0366		-0.0191	
	[0.474]		[0.906]		[0.497]		[0.657]	
a5	-0.0284		-0.0648		-0.0311		-0.0588	
	[0.511]		[0.200]		[0.563]		[0.192]	
a6	0.0107		-0.1019		-0.104		-0.0121	
	[0.803]		[0.045]		[0.055]		[0.787]	
a7	-0.0434		-0.0515		-0.0402		-0.05	
	[0.315]		[0.308]		[0.455]		[0.266]	
a8	-0.0141		-0.0591		-0.0621		-0.1027	
	[0.743]		[0.242]		[0.249]		[0.025]	
a9	-0.0227		-0.1192		-0.0849		-0.0409	
	[0.599]		[0.020]		[0.116]		[0.362]	
a10	-0.0289		-0.0762		-0.0696		-0.0405	
	[0.503]		[0.133]		[0.197]		[0.367]	
a11	0.0107		-0.0614		-0.0534		0.002	
	[0.803]		[0.225]		[0.322]		[0.965]	
a12	0.015		-0.0312		-0.0178		0.0121	
	[0.728]		[0.536]		[0.741]		[0.786]	

Note: This table reports the results for the regression analysis of the January effect. a1-a12 represent dummy variables, and a0 is an intercept term for both regressions. Regression 1 tests the significance of all dummy variables representing February though December. The coefficients and significance are reported for each index in column 1. Regression 2 tests the significance of the January dummy variable on its own. These coefficients and dummy variables are reported in column 2.

The null hypothesis of the first regression requires that all ?$_i$ (i>1) are all zero. This in effect tests all months except January for a seasonal trend. If this hypothesis can be rejected, this would lend support to the theory of seasonal trends on the Warsaw Stock Exchange, since index returns can be predicted with some degree of certainty by simply knowing the month. The second regression equation tests directly for a January effect, by testing only for possible nonzero returns in January and assuming returns in other months essentially equal to zero or at least equal.

Once again, the results for the WIG index closely resemble the results in Henke (2003). The coefficients of the dummy variable for February to December were all negative. However, the coefficients were found to be less significant for the months of June and September. This suggests that as more data points are added to the test, the negative coefficients become less significantly different from 0 for months other than January. Though this is not certain with only two more years of data, it is sensible that seasonal patterns would be diminished. This would especially be true for months other than January, where seasonal trends cannot be explained by yearly events. This is supported by the finding of an equal t-statistic of 1.94 for the intercept return of equation 1, which summarizes the January effect in this equation. In equation 2, the coefficient for the January dummy variable becomes only slightly less significant at 1.48 compared to 1.57 in Henke (2003). However, both of these coefficients did decrease in my results, which is also expected. Since Henke (2003) was a published paper available to investors on the Polish stock exchange, the findings in the paper can be expected to affect investors, and assist in diminishing the effect. This apparent effect is studied with some more detail in a later section of my study, but it is important to note that the WIG regression results are sensible in the context of Henke's paper and the improvement in efficiency it might have caused.

On the other hand, the results for the other indices are somewhat surprising in the context of general January effect literature. The January effect literature often concludes that small stocks should outperform large stocks in January, and that the small stock are largely responsible for the January effect. (Jones, Pearce, and Wilson 1987, p453) However, my results contradict this stipulation for the WSE. The WIG20 index exhibits results from the regression equation closely resembling the WIG index. The WIG20 results could even be interpreted as stronger in finding a January effect since the coefficient of the January dummy variable in equation 2 is significant at the 10% level. The other important statistics are also very similar. This can be largely explained by the significant effect WIG20 stocks have on the WIG index because they are the largest stocks, and are therefore highly represented in the weighted WIG index. However, it is interesting to note that the coefficient of the January dummy variable in equation 2 is both higher and more significant.

Furthermore, the results of the January effect regression on the WIRR and MIDWIG indices are very inconclusive. None of the relevant coefficients are significant for either index. The coefficients are notably smaller and the January dummy variable coefficient is even negative for the WIRR index representing the smallest stocks by capitalization. This is very interesting since it suggests that the January effect is not a significant phenomenon in smaller stocks, though it is certainly significant for the WIG and

WIG20 index, where large companies seem to play a large role in driving the effect.

The last tests conducted by Henke is a simple compilation of daily index returns on the last 5 days of the year and the first 5 days of the year. The results from my study for the WIG, WIG20, WIRR, and MIDWIG indices are summarized in Tables 8a and 8b.

Table 7a. Average daily returns at the turn of the year

		WIG	WIG			WIG20	WIG20		
		Mean	Stdev	t-stat.	Signif?	Mean	Stdev	t-stat.	Signif?
JAN	1ST	0.020624	0.021511	3.456889	1%	0.018564	0.020521	2.860676	5%
JAN	2ND	0.012472	0.020505	2.193042	5%	0.016203	0.024539	2.087961	10%
JAN	3RD	-0.00576	0.023998	-0.86501		-0.00353	0.027765	-0.40184	
JAN	4TH	0.012337	0.021334	2.085067	10%	0.016696	0.023594	2.237725	5%
JAN	5TH	0.00437	0.02481	0.635024		-0.00117	0.025784	-0.1434	
DEC	LAST	0.006748	0.019525	1.246098		0.003979	0.013342	0.943101	
DEC	2ND LAST	-0.01423	0.032696	-1.56975		-0.00137	0.014741	-0.29294	
DEC	3RD LAST	0.017135	0.0284	2.175442	5%	0.010245	0.014969	2.164343	10%
DEC	4TH LAST	0.019094	0.023494	2.930388	5%	0.012704	0.012879	3.119325	5%
DEC	5TH LAST	0.001832	0.020901	0.315992		0.002855	0.013117	0.688195	

Table 7b. Average daily returns at the turn of the year

		WIRR	WIRR			MIDWIG	MIDWIG		
		Mean	Stdev	t-stat.	Signif?	Mean	Stdev	t-stat.	Signif?
JAN	1ST	0.00163	0.016428	0.297577		0.011114	0.01432	2.053259	10%
JAN	2ND	0.00965	0.021671	1.408128		0.006166	0.015657	1.041978	
JAN	3RD	-0.0139	0.021928	-2.00394	10%	-0.00959	0.025457	-0.99714	
JAN	4TH	0.010344	0.013356	2.449117	5%	0.011798	0.018293	1.706417	
JAN	5TH	0.000202	0.027184	0.023454		0.001054	0.018379	0.151665	
DEC	LAST	0.012275	0.014171	2.598656	5%	-0.00031	0.006012	-0.12541	
DEC	2ND LAST	0.010251	0.014896	2.06459	10%	-0.00195	0.00762	-0.6258	
DEC	3RD LAST	0.008299	0.014077	1.76867		0.006328	0.013624	1.13783	
DEC	4TH LAST	0.014595	0.018693	2.342322	5%	0.012362	0.009926	3.050893	5%
DEC	5TH LAST	0.004282	0.021466	0.59851		0.007923	0.008467	2.292168	10%

Note: These 2 tables summarize the results of sample tests of the last 5 days of trading in December and first 5 days of trading in January. For each index, the mean returns for each of these days is reported, followed by the standard deviation of the sample, the Student's t statistic for this mean and the level of significance.

As expected, the results were once again very similar to Henke's (2003) for the WIG index. Notably, the positive return on the second trading day in January became stronger and significant at the 5% level though it was insignificant in the earlier study. Though the average return for the first January trading day slightly diminished, the significance was slightly strengthened. In general, the returns were slightly diminished in this study including 2003 and 2004 data. However, the significance was at least maintained. The large returns in the first 5 days of January are still observed on this data set of 13 years, with a 2.1% return on the first day and a 1.2% return on the second day. As in Henke's paper, the end of December returns are rather mixed between significantly positive returns and the average –1.45 return on the second to last day. Early January returns are still very positive. In general, these results suggest some learning on the part of investors, but the overall effects have been maintained in this data set. As suggested earlier, this learning effect will be delved into further along in the paper.

Like the regression analysis, the WIG20 daily statistics are virtually identical to the WIG results. All the same days are significant, though not necessarily at the same levels. The large and significantly positive return on the first trading day in January is maintained. The mean daily returns are also generally very similar. Furthermore, the WIRR and MIDWIG daily returns are again rather inconclusive. The WIRR does have a strong return on the first trading day in January, though end of December returns are significantly positive and sustained across the last five days of the month. Though the MIDWIG does have a significant positive return of 1.1% on the first trading day in January, the mean returns are generally smaller and less significant than for the WIG or WIG20.

The January effect is certainly present in the WIG, as found by Henke(2003), and reaffirmed with two more years of data in this study. It is also clear from comparing results of different indices that the seasonal effect in the WIG index are driven mostly by the the larger stocks in the WIG20, while the MIDWIG and WIRR are less important to the effects observed in the WIG. The returns of the WIG are expected to closely follow the WIG20, since these large stocks are most influential in the weighted WIG index. However, it is surprising to find that evidence for a January effect is most prevalent in the WIG20, representing the largest companies, while the MIDWIG and even more so the WIRR, return marginal and inconclusive results.

This common result, observed across all of the previous three tests, contradicts January effect theory, which expects the effect to be most prevalent and driven by smaller stocks (Jones, Pearce, Wilson 1987, p453). However, this unusual result could help to explain the effect in Poland. Henke conjectures that the seasonal effect in Poland cannot be explained by tax-loss selling, but can be attributed to a window-dressing by institutional investors. The window dressing effect states that money managers sell losing stocks at the end of the year so their portfolio only contains winners when it is presented to investors in an annual report. He concludes that this is the prevalent effect because “in the continuous trading system until November 2000, a minimum order size applied that amounted to several thousand zlotys and virtually excluded small private investors. Thus, the majority of trades in this trading system can be attributed to institutional investors" (Henke 2003, p9). However, several thousand zlotys amounts to less than 500 USD. This is unlikely to deter many investors even small and private. Furthermore, a brokerage house could pool orders together of the smallest investors, as is done on the NYSE, where stocks must be traded in lots of 100. Furthermore, Table 1 shows statistics from a survey performed by the WSE. The number of institutional investors is now at 37%, but was as low as 22% in 1998-2000. (See Table 1.) Therefore, it seems very unlikely that this inconsequential regulation would be significant enough to conclude that most investors were institutional, especially when one considers the WSE survey. Nonetheless, the consistent 35% of institutional investors are likely to cause some sort of window-dressing effect, and this cannot be completely ruled out.

However a much more important effect not addressed by Henke, is the effect foreign investors have on the WSE. Foreign investors constitute approximately 30% of the total on the WSE. (See Table 1.) This group is certainly significant. Furthermore, investors from many countries, including the US, are subject to tax-loss selling laws. Though their investments are made in Poland, the investor must pay US capital gains tax on these returns. Therefore, this significant portion of investors could certainly effect events on the WSE. Since, a January effect is often attributed mainly to tax-loss selling in developed markets, one can conclude that this effect would be much stronger than a window dressing effect. (Jones, Pearce, and Wilson 1987, 453)

Furthermore, the inconsistently strong January effect in large stocks supports this claim. Though specific statistics concerning which stocks foreigners invest in are not available, one can guess that they prefer large stocks. This is likely since this group is most liquid, and therefore attractive to foreign investors accustomed to high liquidity on home exchanges, and more comfortable with the improved security that the liquidity provides when the market becomes volatile. Furthermore, these large stocks provide the best information to international investors through web pages available in multiple languages and staff knowledgeable in other languages. For these reasons, foreign investors are most likely to flock to the largest, most transparent companies trading on the WSE. The January effect's prevalence in large stocks seems to support the claim that the effect is actually driven by foreign investors and tax-loss selling. The number of foreign investors in Poland and relative strength of a tax-loss selling effect versus a window-dressing effect observed in other studies, suggests that tax-loss selling might play a much more important role in the January effect that was considered by Henke.

Learning on the WSE

The Henke paper became available in February 2003. Even though one can generally expect the January effect to disappear as private parties discover it, the availability of a publicly available paper on the matter should make this certain. However, only one year of data exists after the Henke paper was published. Therefore, any results from January 2004 cannot be conclusive in judging investors' ability to learn on the WSE. However, it can give an idea of what to expect if trends were to continue from 2004 moving forward.

Table 8. 2004 January Monthly and Daily Returns

Index	WIG	WIG20	MIDWIG	WIRR
Monthly Return	0.0527	0.0362	0.1133	0.1331
5th Last	0.001577	0.001793	0.003637	0.013932
4th Last	0.010897	0.010496	0.012955	0.010105
3rd Last	-0.00033	-0.00103	0.001968	0.007327
2nd Last	0.000337	-0.00093	0.003979	0.015686
Last	-0.00202	-0.00142	-0.00179	0.000332
1st	0.02276	0.026797	0.009916	0.022341
2nd	0.033174	0.039791	0.022987	0.024552
3rd	-0.00292	-0.00366	-0.0014	0.003951
4th	0.000864	-0.00141	0.006574	0.011746
5th	-0.00065	-0.00391	0.005951	0.005782

Note: This table reports results from just 2004 for the 4 indicated indices. Row 2 reports the return for January 2004. Rows 3-13 reports the index returns for the last 5 days of December 2003 and first five days of January 2004.

In January 2004, the WIG index experienced a 5.4% increase. Likewise, all the other indices experienced similar positive returns. However, the small stock indices seem to exhibit a more traditional January effect with significantly higher monthly returns for the month of January over the WIG20 stock index. Furthermore, it is very interesting to note how closely the daily returns from 2004 resemble the average daily returns from previous years. This is especially true for the WIG index, which advanced 2.3% on the first trading day of January, and 3.3% on the second day of trading in 2004. Though one certainly cannot make any strong claims from one year of data, these results do give some insight on the January effect in 2004. The data suggests that the January effect persisted, with similar magnitudes and trends as previous years. There seems to be no evidence that investors were able to learn from the January effect paper by Henke. Furthermore, the strong returns in small and mid cap stocks could indicate the evolution of a stronger January effect in this group of stocks in future years. However, none of these claims can be substantiated as of yet.

In January 2004, the S&P 500 index improved by 1.8% and the German DAX index increased approximately 2.9%(Yahoo Finance: "Index Quotations"). These indices represent returns in developed markets, which are unlikely to show signs of a January effect. Therefore, the general improvements in world markets would lead one to expect an improvement in the WIG and other Polish indices. Though the daily returns around the year seem strikingly similar to the average from previous years, one should be especially hesitant to declare this as certain evidence of a continued January effect in light of the world wide strength in capital markets.

January Effect Conclusions

The phenomenon of a January effect has certainly been visible on the WSE over the last 13 years. However, the effect does not take a traditional form on the Warsaw market. The larger stocks represented by the WIG20 have the strongest January effect, while tests of the small cap and mid-cap index are inconclusive. This result suggests the importance of tax-loss selling by foreigners as a main cause of the January effect, unlike Henke's suggestion of a dominant window-dressing effect by institutional investors. The results from 2004 suggest that a January effect persists, and certainly cannot be ruled out yet.

The January effect in Poland is important both from a theoretical and practical perspective. The existence of a January effect suggests that capital markets do not accurately transfer information to the economy about the market between investors and capital issuers. Since January returns can be predicted, the market price is not incorporating all available information. If market participants were fully aware of this effect they would buy at the end of December to take advantage of this effect created by certain investors taking advantage of tax laws in foreign countries.

The January effect is an example of weak- form inefficiency since January returns are not random, and can be predicted with the use of past price trends. Any such weak form inefficiency presents a problem to a market's ability to accurately reflect the investor/capital relationship. The existence of inefficiencies leaves economic participants questioning the price information supplied by the capital market because the market does not incorporate the observed January effect. If it did, the effect would disappear. This increases risk and deters free market transactions since participants require higher returns from projects to justify the excess risk from inaccurate capital prices.

The January effect in Poland also provides a trading strategy by which investors can outperform market return. The average return in January for the WIG and WIG20 is 7.0% and 6.1% respectively. Though an investor is not guaranteed to make a profit by investing in these indices every January, they have a much higher likelihood of profiting in January than any other month of the year. Furthermore, a trading strategy, which advises investors to only invest in Poland for the month of January, outperforms a buy and hold strategy because one is able to lock in the expected gains from January without taking on risk for the other months of the year. Therefore, this weak-form inefficiency can assist investors in their trading strategy as long as expected returns in January exceed the expected return of other months, which was shown to be insignificantly different from 0 by most of the tests. However, as the January effect becomes better understood, the phenomenon will begin to diminish and eventually disappear since investors will try to buy before January or late December to take advantage of the expected high returns. These investors will sell their short term holdings in January, and eventually this sell pressure will equal the buy pressure currently observed on the WSE at the beginning of the year.

Though the January effect was originally observed in the US, it has now disappeared. As investors attempted to take advantage of the higher expected returns, the phenomenon was diminished and eventually erased. (Yanxiang Gu, Anthony 2002) Interestingly enough, the January effect in the US markets had practically disappeared by the time it was publicly observed. Though the WSE is only 13 years old, the methods and tools available to investors and market researchers is similar to those in the US. The January effect was even observed in a publicly available paper in 2003. However, the effect certainly seems significant in the tested data set, and does not seem to have given up in 2004. Unfortunately, tests of a January effect were not available for other emerging capital markets, and the WSE results cannot be compared to markets of similar age.

The January effect is a phenomenon that disappears when market participants are reasonably aware of its existence. Investors on the WSE most likely do not consider it because Poland does not have any capital gains taxes. However, tax-loss selling effect caused by foreign investors and window-dressing effect from institutional holders is sufficient to cause a January effect. The US capital market's eradication of the January effect provides a model for the WSE. Education is the answer, not regulation. By educating the market participants of this inefficiency, it will be erased. The convergence with weak-form market efficiency is important to a developing economy's viability, and is best achieved by taking advantage of market forces.

2. Weak Form Tests of Market Indices

A standard indicator for a market's weak form efficiency has become the results of index tests. Since most emerging capital markets do not make detailed stock data available, these general index tests become the best indication of a capital market's efficiency. While the WSE data allows this study to perform more pointed and detailed research, this is often not possible. The weak form tests of index return give an important general idea of market efficiency, as well as a comparison to other printed results. This comparison of like results will best allow for an accurate comparison of the WSE to other emerging and developed markets.

As described in the methodology section of this paper, an autocorrelation test and runs test are performed on index results from the WIG, WIG20, WIRR, and MIDWIG indices.

Table 9a. Autocorrelation and Runs Results for Indices

INDEX		WIG	TECHW	MIDW	WIRR	WIG20
ICEPTION DATE		04/16/91	12/29/99	12/31/97	01/02/95	04/16/94
END DATE		03/31/04	03/31/04	03/31/04	03/31/04	03/31/04
PERIOD 13	k=1 AC	0.001			0.01	0.001
10/01/94	RUNS	0.99			0.95	0.99
02/03/97	N	581	<5	<5	520	581
PERIOD 14	k=1 AC	0.05		N/A	N/A	0.05
02/03/97	RUNS	0.99		N/A	N/A	0.99
01/16/98	N	237	<5	9	237	237
PERIOD 15	k=1 AC	0.001	N/A	0.001	0.001	0.001
01/16/98	RUNS	N/A	N/A	N/A	0.95	N/A
11/26/01	N	968	478	968	968	967
PERIOD 16	k=1 AC	0.001	0.001	0.001	N/A	N/A
11/26/01	RUNS	0.9	N/A	N/A	0.99	N/A
04/01/04	N	587	587	587	587	587
PERIOD 17	k=1 AC	N/A	N/A	0.001	0.001	N/A
01/01/03	RUNS	0.9	N/A	0.95	0.99	N/A
04/01/04	N	315	315	315	315	315

Note: These tables report the autocorrelation and runs test results for market indices. The first row for each period gives the significance of the autocorrelation test for a lag of 1. The second row for each period gives the significance for the runs test, and the third row gives the number of observed data points.

Table 9b. Autocorrelation and Runs Results for Indices

INDEX		WIG	MIDW	WIRR	WIG20
START DATE		04/16/91	12/31/97	01/02/95	04/16/94
END DATE		03/31/04	03/31/04	03/31/04	03/31/04
PERIOD 1	k=1 AC	0.05			
04/16/91	RUNS	N/A			
01/01/92	N	35	<5	<5	<5
PERIOD 2	k=1 AC	0.001			
01/01/92	RUNS	N/A			
01/01/93	N	100	<5	<5	<5
PERIOD 3	k=1 AC	0.001			N/A
01/01/93	RUNS	0.99			N/A
07/01/94	N	229	<5	<5	32
PERIOD 4	k=1 AC	N/A			N/A
07/01/94	RUNS	N/A			N/A
10/01/94	N	51	<5	<5	51
PERIOD 5	k=1 AC	0.001		0.05	0.001
10/01/94	RUNS	0.99		0.95	0.99
07/08/96	N	438	<5	377	438
PERIOD 6	k=1 AC	0.001		0.01	0.001
10/01/94	RUNS	0.99		0.95	0.99
02/03/97	N	620	<5	559	620
PERIOD 7	k=1 AC	0.001		0.05	0.001
04/16/91	RUNS	0.99		0.95	0.99
07/08/96	N	853	<5	377	521
PERIOD 8	k=1 AC	0.001		0.01	0.001
04/16/91	RUNS	0.99		0.95	0.99
04/01/97	N	1035	<5	559	703
PERIOD 9	k=1 AC	0.001	0.001	0.001	0.001
07/08/96	RUNS	0.99	N/A	0.9	0.99
11/17/00	N	1091	720	1091	1091
PERIOD 10	k=1 AC	0.001	0.001	0.001	0.001
04/01/97	RUNS	0.95	N/A	N/A	0.95
11/17/00	N	909	720	909	909
PERIOD 11	k=1 AC	0.01	0.001	N/A	0.05
11/17/00	RUNS	N/A	0.95	0.99	N/A
04/01/04	N	844	844	844	843
PERIOD 12	k=1 AC	0.001	N/A	0.001	0.001
04/16/91	RUNS	0.99	0.9	0.99	0.99
04/01/04	N	2788	1564	2312	2455

Note: These tables report the autocorrelation and runs test results for market indices. The first row for each period gives the significance of the autocorrelation test for a lag of 1. The second row for each period gives the significance for the runs test, and the third row gives the number of observed data points.

The results in Tables 9a and 9b report the the level at which the one lag autocorrelation test was significant, the significance of observed runs versus expected, and the number of data points for each test.

WIG Index Results

Though reporting all of the indices can help pinpoint market inefficiency local to certain stock segments, the results of the WIG index are most important for comparisons with other exchanges since this index most closely resembles the all-share indices tested for weak-form efficiency on other exchanges. The WIG index has autocorrelation in the residuals of at least 5% significance of every period, except the fourth and seventeenth. The insignificant autocorrelation of the fourth period can be explained by the few data points available for testing the period of four trading days per week. The 51 data points make finding significant results difficult. Therefore, this observation is most likely unimportant since other periods that include the four trading day period exhibit significant autocorrelation.

However, the observation of insignificant autocorrelation in period 17 is more meaningful. Period seventeen represents the last 15 months of data available (01/01/03 – 04/01/04). This period has 315 data points, which is more than a number of other periods tested. Therefore, this result can not be easily dismissed. Though 1/1/03 does not represent any event in the history of the WSE, this period was tested for the current state of market efficiency, as represented by a set of the most current returns.

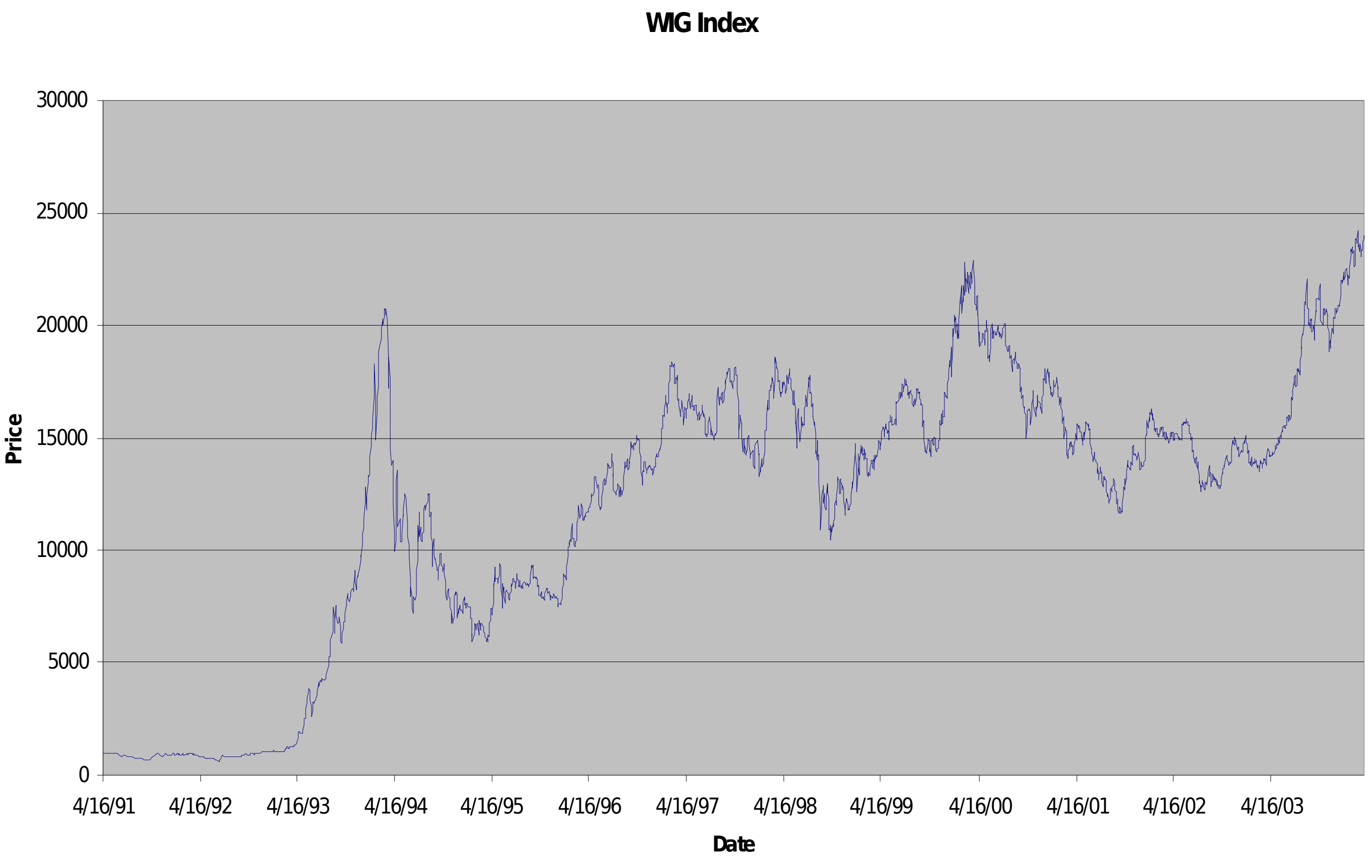
Of all the periods tested, only one other had more than 300 observations and a significance of less than 0.1%. This is period fourteen which tests the indices after the introduction of the WARSET system. Though the WIG index was most certainly inefficient in this period, the introduction of the WARSET system seemed to improve efficiency on the exchange as a whole, though only slightly.

However, the effect of the WARSET system on efficiency is very clear in the WIG20 results. The WIG20 was immediately impacted since its constituent stocks were the first to enter continuous trading through the WARSET system. When the WARSET system was first introduced, a small percentage of WIG stocks traded on it. However, this number has steadily increased and today all the 98 members of the WIG trade on the WARSET system. (Warsaw Stock Exchange: "Indices") This is the most likely explanation for the completely insignificant results for weak-form efficiency test in the last 15 months. This is also logically sensible knowing the effect the WARSET system had on the WIG20 and that WIG constituents were phased into the WARSET system over the last three and a half years.

The weak-form efficiency of the WIG index over its whole life is tested by Period 12 above. The results show autocorrelation of residuals at the 0.1% confidence level, and the existence of runs at the 99% level. This certainly suggests the market index has been weak-form inefficient over its life span. Since these strong results in the autocorrelation test persisted in almost all the sub-periods, the findings are substantiated and show little improvement in efficiency with the exception of the last 15 months. The runs test has more variance in the results, but shows that runs did remain even in the last 15 months (at the 90% confidence level).

The period breakdown of the study was done with the purpose of isolating specific times and factors, which might have induced or minimized inefficiency. Periods 1-5 test for efficiency improvements as trading days were added to the exchange. There were no significant differences in the WIG index results.

Chart 1. WIG Index Prices



Note: This chart represents the WIG index returns from 1991 to 2003. It is compiled from the index data used for this study.

WIG20 Results

The WIG index tests were done under slightly higher scrutiny to test for any effect the introduction of futures might have to efficiency.

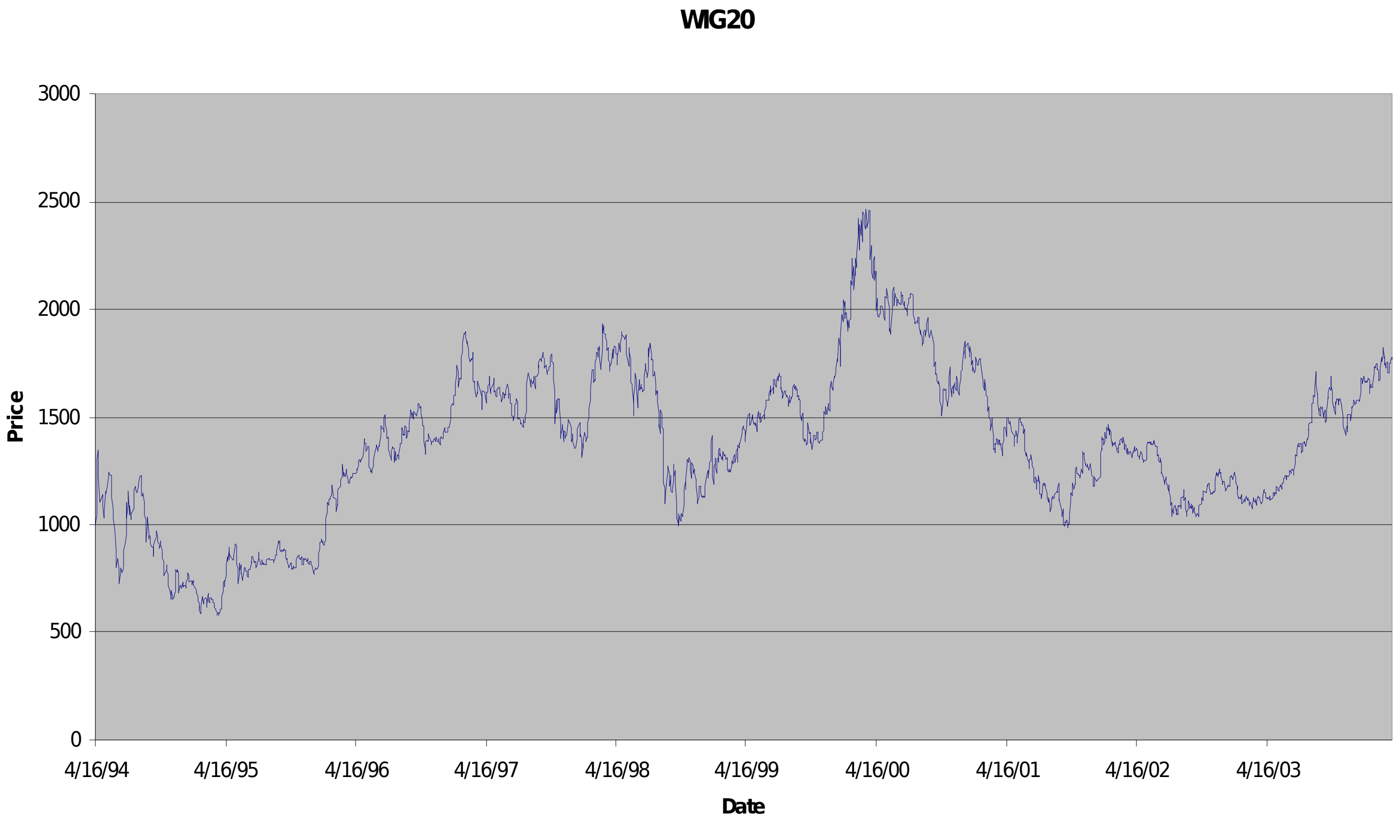
Table 10. WIG20 Autocorrelation and Runs Test Results

WIG20		
PERIOD 18	k=1 AC	0.001
04/16/94	k=2 AC	0.001
02/03/97	RUNS	0.99
	N	665
PERIOD 19	k=1 AC	0.05
02/03/97	k=2 AC	N/A
01/16/98	RUNS	0.99
	N	237
PERIOD 20	k=1 AC	0.001
01/16/98	k=2 AC	0.001
11/17/00	RUNS	N/A
	N	711
PERIOD 21	k=1 AC	0.001
01/16/98	k=2 AC	0.001
11/26/01	RUNS	N/A
	N	967
PERIOD 22	k=1 AC	N/A
11/17/00	k=2 AC	N/A
04/01/04	high lag	N/A
	RUNS	N/A
	N	778
PERIOD 23	k=1 AC	N/A
11/26/01	k=2 AC	N/A
04/01/04	RUNS	N/A
	N	522
PERIOD 24	k=1 AC	0.001
04/16/94	k=2 AC	0.001
04/01/04	RUNS	0.99
	N	2391

Note: These tables report the autocorrelation and runs test results for the WIG20 index. The first row for each period gives the significance of the autocorrelation test for a lag of 1, and the second row reports the same for a lag of 2. The third row for each period gives the significance for the runs test, and the fourth rows gives the number of observed data points.

However, over its lifespan, the index experiences autocorrelation at the 0.1% level and runs at the 99% significance level, indicating weak-form inefficiency over the life of the index. However, the WIG20 has some interesting period results. Contrary to expectations, the WIG20 becoming continuously quoted, the introduction of WIG20 futures, and introduction of MiniWIG20 futures was not important to the significance of weak-form efficiency. Like the WIG index, autocorrelation becomes less significant in the period when the WIG20 becomes continuously quoted and real-time Reuters data was introduced. Though both of these events would logically be consistent with improvements in efficiency, the significance of these events seems unlikely since the index reverts to more significant weak-form inefficiency in the next period (the introduction of the WIG20 future). Period 19 seems to be characterized by more random movement and no significant trend in one direction, as depicted in Chart 2.

Chart 2. WIG20 Index Price Chart



Note: This chart represents the WIG index returns from 1991 to 2003. It is compiled from the index data used for this study.

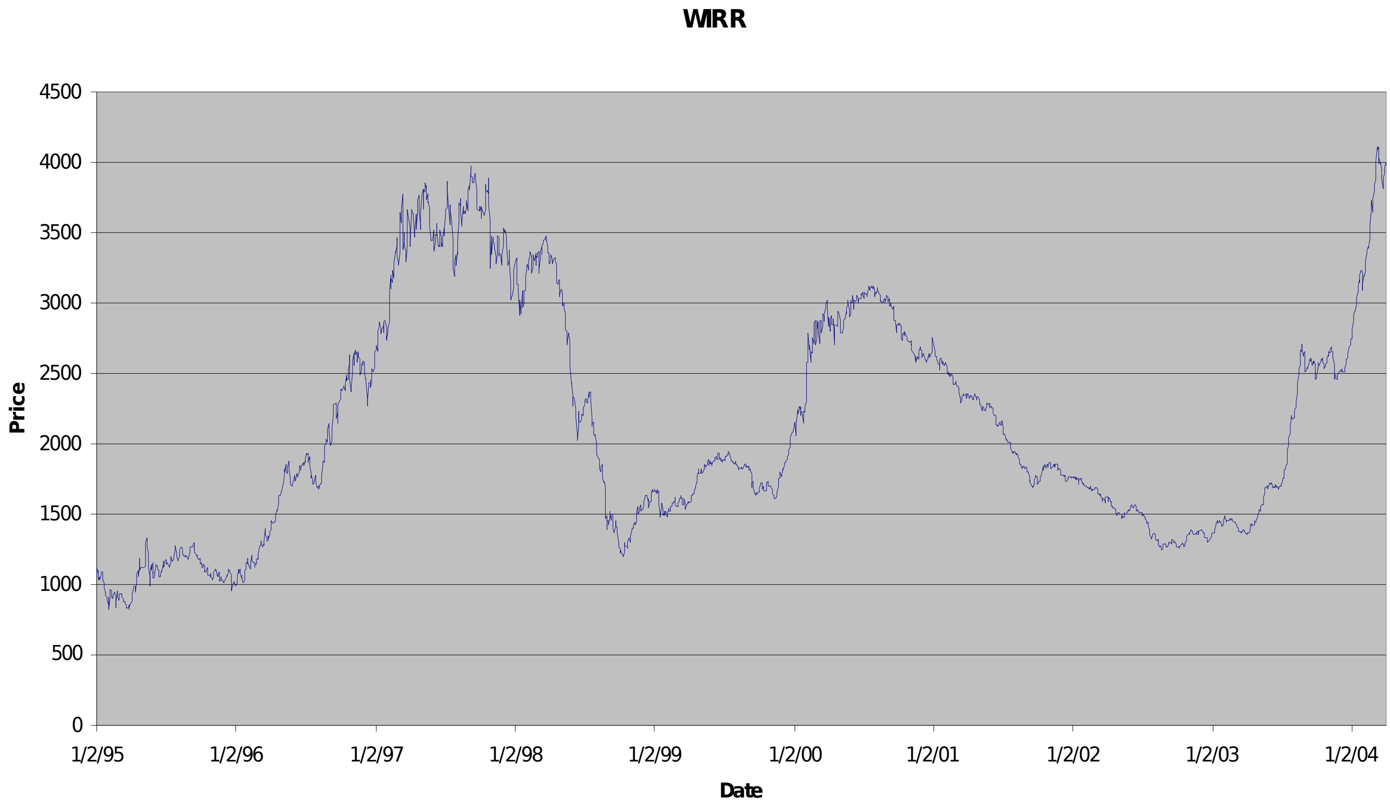
Thus, the seeming improvement in period 19 efficiency is most likely insignificant to draw conclusions about the effect of Reuters data and introduction of real-time quotations of the WIG20 index.

11/17/00 does however seem to be a very significant date for the WIG20 index. After this date, no autocorrelation of residuals was observed and runs were found to be insignificantly different than the expected, as shown in the results from periods 22 and 23. On this date, the WARSET system was introduced, and it clearly had a very significant impact on the WIG20 constituent stocks. The WIG20 index represents the large cap companies with the highest market turnover. Likewise, these would be the first companies introduced to the WARSET system, a continuously traded market segment featuring rapid market access and improved information. Therefore, it is quite clear from these results that the WARSET system was very significant in improving the weak- form efficiency of this segment of stocks. This is certainly the most clear cut result from the WIG20 index test and it has several important implications to this research.

WIRR index

The results for the MIDWIG and WIRR indices are somewhat more sporadic, and do not paint as clear a picture of changes in market efficiency. Over its entire life, the WIRR is shown to be inefficient at the 0.1% significance level. However, the periods in which the index is not significantly weak form efficient seem somewhat random. These include period 11, 14, and 16. Less significant efficiency in period 14 is common across all the indices. However, it cannot be easily explained because it is followed by continued inefficiency, and no policy or regulation changes could have conceivably caused this.

Chart 3. WIRR Price Chart



Note: This chart represents the WIG index returns from 1991 to 2003. It is compiled from the index data used for this study.

However, Chart 3 shows it as a relatively steady period, in which prices did not move significantly in one direction or another, and the price movements were seemingly random. Likewise, the insignificant inefficiency in periods 11 and 16 is not easily explained because the index reverts to a period of significant autocorrelation of residuals and runs in the following period, which represents the last 15 months of data. It is interesting to note that this index is not weak form efficient in the last tested period like the WIG and WIG20 indices. This can also be explained by the importance of the WARSET system. Since, most of the WIRR stocks continue to trade on the WSE's auction system, they cannot take advantage of the rapid order processing, untampered pricing, and full market information available through the WARSET system. Therefore, these groups of stocks continue to exhibit weak-form inefficiency even today.

MIDWIG index

The MIDWIG index results present a strange curiosity, in that the autocorrelation for the life of the index is found to be insignificant. However, the individual sub-periods are all significant with the exception of Period 14. The MIDWIG has only 9 data points in this period and this should not significantly effect the results for the whole data set. Though this cannot be explained within the context of this analysis, the individual periods are all individually significantly inefficient. Like the WIRR, the MIDWIG remains weak-form inefficient at the 0.1% level in the most recent period (17).

Index Test Conclusions

The weak-form efficiency tests of WSE indices represent some very interesting results relevant to the objective of this paper. First of all, the WIG20 index result indicates the importance that the introduction the WARSET system had on the WSE. The importance of this system to weak-form efficiency is further justified by its effect on the WIG index, as this index's constituents were integrated into the WARSET system. Furthermore, the sporadic results from the WIRR and MIDWIG indices both confirm the maintained inefficiency in the smaller stocks of the WSE even today. This can be explained by the continuation of a call auction system for these more illiquid stocks. Nonetheless, this result does have importance to the state of weak- form efficiency on the WSE.

The most conclusive result from these tests is the effect of the WARSET system on weak form efficiency. This result should serve as a prescriptive measure for both the WSE and other emerging capital markets. Efficiency is an often lofty goal for these markets that is not easily attained. Their inefficient markets deter investors and also prove an expense to their capital system with the additional uncertainty and risk it creates. These markets strive to mimic the highly efficient developed markets, like those in the US, as is clear in the setup of Poland's capital system with its regulatory bodies and encouragement of free market practices. However, these goals are often not easily met. With the introduction of the WARSET system, the WSE was able to quickly transform itself into a weakly efficient marketplace. This integration to an electronic trading system should continue to include the newer, smaller stocks. Then, the WSE could boast efficiency throughout its listed securities. Likewise, other emerging markets can learn from Poland’s experiment. The implementation of an established trading system, like that of Poland, can quickly improve efficiency. With improved efficiency, the markets can continue to grow into viable institutions.

The index results presented here all suggest the existence of market inefficiency in much of the history of the WSE. However, much of this has been ammended for the largest, most traded stocks. Therefore, the market as a whole does a much better job of representing the capital market effectively and accurately for the whole economy. However, the inefficient capital market for smaller and newer companies has yet to be improved. This would allow investment into this segment with less risk for investors.

However, the autocorrelation and runs observed for this market segment does have another important implication for investors. Abnormal returns can be attained within this market segment by expecting price returns to trend in one direction. These significant trends can be implemented to outperform the market return on a risk adjusted basis. However, the ability to profit from such trends will be better explained by the results from individual stocks over daily and weekly periods.

Emerging Market Comparisons

Lastly, the index results serve as a measure of comparison to other emerging and developed exchanges. The two sources by which these index results can be best compared come from El-Erian and Kumar (1995) focusing on Middle Eastern markets, and Magnusson and Wydick's (2002) work on African markets. These papers both conduct similar weak form efficiency tests. However, the data sets are much more constrictive, and each study uses only two to five years of data.

The results in El-Erian and Kumar (1995) are somewhat out-dated. However, it serves as an interesting comparison because each of the markets were at least as old as the WSE is today at the time of the study, including an Egyptian market more than 100 years old. The study performs both autocorrelation and runs tests of the available indices. Of the Middle Eastern markets, Jordan and Turkey represent the most highly developed and liquid exchanges. However, both of these markets are found to have significant serial correlation of returns in an autocorrelation of residuals test implemented for the WSE as well. Furthermore, the runs test showed the markets in Jordan and Turkey to be inefficient at the 5% and 1% significance levels, respectively. As a mode of comparison, the same tests were carried out for the Greek, Indian, and Philippine exchange, which are other developing capital markets in other sections of the world. Of these, only the Philippine market experienced correlation of residuals, and both the Philippine and Greek exchanges were found to be inefficient under the scrutiny of a runs test.

The weak- form efficiency of Jordanian and Turkish capital markets is comparable to Poland at the time. However, Poland's best representative index, the WIG, has since experienced a significant improvement in weak- form efficiency. The significant improvement has been driven by the WARSET system and the large, liquid stocks which trade on it. Therefore, it is relatively safe to say that the WSE has significantly outperformed the Middle Eastern markets in terms of weak form efficiency improvement in a shorter period of time. This is especially true considering that Jordan and Turkey are the most developed markets of the region. However, the Greek and Indian exchanges seem to be of a similar degree of efficiency Poland at the time. However, a comparison of these markets in 1995 and the WSE today is likely not very meaningful since the results do not exhibit glaring differences. The small data set available in the 1995 study, and the differences between the indices in representing their corresponding markets makes such a comparison relying on intricate details rather irrelevant.

Magnusson and Wydick's (2002) research provides further results for emerging and developed capital markets. Though their results are up to date, they do not conduct runs tests on their samples. Like the Jordan and Turkey research, this study focuses on indices reflective of the entire financial markets. This study looks predominantly at 8 African markets and finds 5 to be weak-form efficient at the 95% confidence level. The results from the WIG and WIG20 find the exchange to be inefficient at this level across its lifespan. However, the WSE has shown great improvement and both would be found efficient if only the last 15 months of data were included. Of the other emerging markets included in their study, Chile, Mexico, and Indonesia were found to be inefficient at the 95% confidence level. However, for the more established markets, like those in Korea, Argentina, and the US, the random walk hypothesis could not be rejected. These results are very general, but they do offer some statistics on emerging and developed markets. Developed markets seem to be weak- form efficient across the board, while newer capital markets have mixed results. The WSE seems to be among the higher tier of new markets making improvements in market efficiency. However simple index tests are not sufficient to declare a market weak form efficient, and the individual stock tests introduced in this paper provide more detailed information on the WSE that is not available for many emerging markets. Therefore, it is currently not possible to draw more meaningful comparisons with these markets.

3. Weak-form Efficiency in Continuous Stocks

While the index results for weak- form efficiency give some insight into the status of the WSE, these results average out a significant amount of inefficiency created by individual stocks. Therefore, this study expands the tests for each stock that has traded on the WSE. The results of the index tests suggest the importance of the WARSET system to market efficiency. For this reason, the study of individual stocks breaks the test down into stocks traded on an auction trading system and stocks traded in a continuous trading system. The statistics from these two groups of stocks will give more information on the importance of such a system in individual stock trading. Furthermore, the data grouped together is useful in giving a better picture of the WSE as a whole.

Table 11. Tests for Continuously Traded Stocks (Daily Returns)

INDIVIDUAL PERIOD STATS		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 6 STATS	Actual	0	1	2	19	18	17	22
	%	0.00%	4.55%	9.09%	86.36%	81.82%	77.27%	
PERIOD 10 STATS	Actual	5	13	30	108	105	97	113
	%	4.42%	11.50%	26.55%	95.58%	92.92%	85.84%	
PERIOD 11 STATS	Actual	40	61	85	194	183	171	224
	%	17.86%	27.23%	37.95%	86.61%	81.70%	76.34%	
PERIOD 12 STATS	Actual	37	58	91	214	208	201	239
	%	15.48%	24.27%	38.08%	89.54%	87.03%	84.10%	
PERIOD 13 STATS	Actual	0	1	1	19	18	17	21
	%	0.00%	4.76%	4.76%	90.48%	85.71%	80.95%	
PERIOD 14 STATS	Actual	4	12	17	41	37	34	46
	%	8.70%	26.09%	36.96%	89.13%	80.43%	73.91%	
PERIOD 15 STATS	Actual	18	26	54	156	152	143	181
	%	9.94%	14.36%	29.83%	86.19%	83.98%	79.01%	
PERIOD 16 STATS	Actual	32	47	78	178	170	160	208
	%	15.38%	22.60%	37.50%	85.58%	81.73%	76.92%	
PERIOD 17 STATS	Actual	28	42	76	146	132	121	197
	%	14.21%	21.32%	38.58%	74.11%	67.01%	61.42%	

Note: This table summarizes the results of tests on individual continuously traded stocks' daily returns. The results are broken down into period, and all periods which data was collected are included in the table. The first three result columns represent significant autocorrelation at the 5%, 1%, and 0.1% significance levels. The next three represent the existence of significant runs at the 90%, 95%, and 99% significance levels. The last column gives the total number of stocks with valid results from the specific period. The first row for each period give the actual number of stocks with observed autocorrelation or runs at the specific significance level, while the second row give the percentage that these stocks are of all stocks with valid results for a given data set.

Daily Return Results

The statistics in Table 11 represent the most relevant results from the continuously traded stock classified by period. Period 12 represents the results for the entire data set of each individual stock when tested for autocorrelation and runs like the WIG index in the earlier test. The first three columns of results represent the percentage of these stocks to experience autocorrelation at the indicated significance level. Only 15.48% of continuously traded stocks were found to have autocorrelation of residuals at the 0.1% level. However, the runs test seems to suggest weak-form inefficiency is certainly present in these stocks. 84.1% of continuously traded stocks were found to have an observed number of runs significantly different than the expected at the 99% confidence level. This is a strong result showing extended runs to be common in these stocks throughout their existence on the WSE. The strong runs results seems to suggest that stock prices are random most of the time, but become serially correlated in bursts (El-Erian and Kumar 1995). Furthermore, the runs test is not concerned with the size of a price change, and only tests for sequential moves in one direction. The strong runs results suggest that stocks are likely to move in one direction more often than would be expected by a random walk. However, the weaker results from the autocorrelation test suggest that the size of these moves is more random, though they tend to continue in one direction.

The results for the last full year of data closely resemble those for the whole data set. Autocorrelation occurs in 14.2% of the stocks at the 0.1% significance level and runs are significantly different in 61.42% of the stocks at the 99% confidence level. The same explanation can be offered for this period as above, though it certainly seems that efficiency improved by the last year of available data.

The periods were broken down with the intention of isolating the importance of events and changes for weak-form efficiency on the WSE. Periods 6, 10, and 11 test for the effect of better information on stock efficiency. The results include not only individual statistics for each period, but also show how efficiency improved or deteriorated for an equivalent group of stocks. This comparison of like groups is more relevant to drawing comparisons about changes over periods.

In period 6, the exchange does not provide significant and detailed real time data on these continuously traded stocks. One can see that in this period, only 4.6% of stocks experience autocorrelation significant at the 1% level. However, 81.82% are observed to have significant runs. During this time period trading was generally light in the continuous trading system. Therefore, volume, liquidity, and price changes were all low. Therefore, the infrequent changes in stock prices yield a result that offers little support for serial correlation in price changes. However, the runs test is not concerned with price changes, and only tests for sequential moves in one direction. This test would detect serial correlation in price changes even if they were infrequent and seemingly insubstantial. The runs test suggests that the direction of price changes is highly predictable, though their size and frequency are more random. Therefore, these stocks can be said to be highly inefficient by this measure.

In period 10, real-time data becomes available through the Reuters service. This is a commonly used data service by traders internationally. This event should make data much more available to investors. In theory, this should increase interest and efficiency since timely better information is available to investors and less risk is involved. The statistics for period 10 from Table 11 actually suggest stocks became more inefficient in this period. The group of stocks available in period 6 supports this to a higher degree. 22.7% of these stocks have autocorrelation at the 1% significance level and 100% experienced runs at the 99% confidence level. (See Table 12.) These odd results suggest that the introduction of Reuters data was not a significant event in improving market efficiency.

Table 12. Daily Statistics for Period 6 Stocks Going Forward

PERIOD 6 STOCK CHANGE		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 6 STATS	Actual	0	1	2	19	18	17	22
	%	0.00%	4.55%	9.09%	86.36%	81.82%	77.27%	
PERIOD 10 STATS	Actual	4	5	8	22	22	22	22
	%	18.18%	22.73%	36.36%	100.00%	100.00%	100.00%	
PERIOD 11 STATS	Actual	6	9	10	17	16	11	19
	%	31.58%	47.37%	52.63%	89.47%	84.21%	57.89%	

Note: This table summarizes the results of tests on individual continuously traded stocks' daily returns. The stocks tested are those with valid data in period 6. Therefore, this table summarizes how this group of stocks changed between the periods. The format is equal to Table 11.

Period 11 represents the introduction of the WARSET system to trading, which was already shown to be a very significant event for the efficiency of WSE indices. The WARSET system provided investors with even better and more detailed information directly from the market. However, it is probably more important that the electronic system improved market access by investors. The results for individual stocks are however not nearly as clear as those from the indices. For all the stocks trading in this period, Table 12 shows the runs results to be comparable to period 6 and the autocorrelation to be more prominent. However, the group of stocks trading since period 6 experienced a significant drop down to 57.9% (at the 99% confidence level) in the percentage experiencing runs. Furthermore, both the group of stocks trading in period 6 and 10 were observed to have more significant autocorrelation of residuals. (See Table 14 for period 10 stock results.) These results suggest that individual stock returns do not suggest a significant impact from the introduction of the WARSET system on weak- form efficiency. It is important to note that these stock returns are limited by the 10% limit on price moves. The exact importance of this regulation will be discussed further in the next section.

Table 13. Daily Statistics for Period 10 Stocks Going Forward

PERIOD 10 STOCK CHANGE		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 10 STATS	Actual	5	13	30	108	105	97	113
	%	4.42%	11.50%	26.55%	95.58%	92.92%	85.84%	
PERIOD 11 STATS	Actual	24	37	48	88	83	75	98
	%	24.49%	37.76%	48.98%	89.80%	84.69%	76.53%	

Note: This table summarizes the results of tests on individual continuously traded stocks' daily returns. The stocks tested are those with valid data in period 10. Therefore, this table summarizes how this group of stocks changed between the periods. The format is equal to Table 11.

The second group of tests looks for improvements in efficiency as changes are made to market indices and futures. Theoretically, improvement in relating information on the market should reduce risk to investors because they are more confident in the general market returns. Therefore, efficiency should improve as market information improves from indices and futures.

Period 13 tests the period before the WIG20 became continuously quoted. It provides the control group for these tests. The results are very similar to those for period 6 since the periods have significant overlap. The percentage of significant autocorrelation is very low, while runs are common and prominent, as seen in Table 11. In period 14, the WIG20 becomes continuously quoted. This index serves as an important benchmark for the WSE even though it only includes 20 large, high turnover companies. In this way, it is rather similar to the Dow Jones Industrial Average for the NYSE. Period 14 shows the whole group of stocks have generally increased autocorrelation and reduced runs. The group of stocks from the first control period shows a similar, unremarkable trend. The introduction of a continuously priced WIG20 index does not seem to have immediate effect on continuously traded stocks.

Table 14. Daily Statistics for Period 13 Stocks Going Forward

PERIOD 13 STOCK CHANGE		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 13	Actual	0	1	1	19	18	17	21
	%	0.00%	4.76%	4.76%	90.48%	85.71%	80.95%	
PERIOD 14	Actual	3	5	7	20	18	16	21
	%	14.29%	23.81%	33.33%	95.24%	85.71%	76.19%	
PERIOD 15	Actual	3	4	7	20	19	18	21
	%	14.29%	19.05%	33.33%	95.24%	90.48%	85.71%	
PERIOD 16	Actual	3	5	7	14	13	11	16
	%	18.75%	31.25%	43.75%	87.50%	81.25%	68.75%	

Note: This table summarizes the results of tests on individual continuously traded stocks' daily returns. The stocks tested are those with valid data in period 13. Therefore, this table summarizes how this group of stocks changed between the periods. The format is equal to Table 11.

Table 16. Daily Statistics for Period 14 Stocks Going Forward

PERIOD 14 STOCKS CHANGE		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 14	Actual	4	12	17	41	37	34	46
	%	8.70%	26.09%	36.96%	89.13%	80.43%	73.91%	
PERIOD 15	Actual	4	6	13	41	40	38	46
	%	8.70%	13.04%	28.26%	89.13%	86.96%	82.61%	
PERIOD 16	Actual	8	13	19	36	35	33	40
	%	20.00%	32.50%	47.50%	90.00%	87.50%	82.50%	

Note: This table summarizes the results of tests on individual continuously traded stocks' daily returns. The stocks tested are those with valid data in period 14. Therefore, this table summarizes how this group of stocks changed between the periods. The format is equal to Table 11.

Period 15 represents the introduction of a WIG20 future. In the US, stock index futures trading is very significant and often drives the moves in the stock market. Likewise, the availability of this future to stock trading on the WSE should improve investors' information and trust of general market prices. Likewise, the introduction of a MiniWIG20 index, in period 16, should improve information since future trading becomes more accessible to all investors with the smaller contract size MiniWIG20. This should again improve the trust in general market pricing since the market values it as such in a futures market. However, Tables 12, 15 and 16, all show insignificant changes in autocorrelation and runs results in these periods.

The WSE, as represented by results from continuously traded stocks, shows convincing signs of weak- form inefficiency. This is especially true of results from the runs test, and somewhat less so from the autocorrelation of residuals test. In general, the improvements in information do not seem to have immediate impact on efficiency in the trading of these equities. Even the introduction of the WARSET system does not show very significant results. However, the measures of efficiency are certainly improved for the last year of data over the majority of other sub-periods. It seems that all of these improvements in information have taken some effect on the market by now, though not immediately. Since market participants cannot immediately take advantage of improvements in information, the effects are not immediately felt. Furthermore, only a liquid and active futures market accurately represents the capital market. Thus, the WIG20 futures might not be useful if the futures market itself is not efficient. The results suggest that these improvements seem to take hold over time on the WSE, as their effects are beginning to be observed in the improved weak-form efficiency of continuously traded stocks only in very recent times.

In general, the results presented here also shed light on the WSE's ability to accurately represent the Polish capital market. While the information that one can gather from market prices has improved, price changes still experience significant serial correlation and consequently prices cannot be fully trusted to fully incorporate all information. Therefore, these prices reflecting the capital market are inaccurate to a certain degree. From an individual stock basis, the WSE has not been able to achieve an efficient equity market that transfers accurate and secure information to the rest of the economy.

Weekly changes

However, as was noted earlier, the results presented above do not reflect the ability of an investor to systematically profit on the WSE. This distinction is entirely the result of the exchange's

10% price move limit. The regulation pretty much guarantees serial correlation to be observed in price moves because the market is not able to fully reflect all information and investor sentiment. Therefore, this will predictably lead the market to require multiple days to factor in information. Since liquidity is almost certain to dry up once the price hits the 10% limit since an investor cannot easily profit from such an occurrence. For example, if investors believe a stock should move up 15% over the last price on newly available information, the price will only be able to move up 10% on that day. Once it hits that 10%, there will be no participants willing to sell at that price because all market participants know the stock should be valued higher and will almost certainly move up further on the next day. Therefore, knowing that a stock is likely to experience a price increase after a 10% move is common knowledge and not useful in making a systematic profit. The weak- form efficiency results are likely caused primarily by this effect and consequently do not provide any significant information, which an investor can find useful.

To test serial correlation in stock prices, discounting for the 10% limit, this study is expanded to tests of weekly price changes. Over a week's time, the effect of any information should be able to factor into the price completely in most cases. Therefore, the effect of this regulation is minor in this study. The results from these tests will allow one to conclude if serial correlation exists even when prices do not hit the 10% limit, since accumulating over a period of one week is likely to control for this regulation. These results should be most interesting to investors seeking out profitable trading strategies.

Table 16. Tests for Continuously Traded Stocks (Weekly Returns)

INDIVIDUAL PERIOD STATS		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD	Actual	0	0	0	7	7	3	22
6 STATS	%	0.00%	0.00%	0.00%	31.82%	31.82%	13.64%	
PERIOD	Actual	1	6	20	52	36	19	113
10 STATS	%	0.88%	5.31%	17.70%	46.02%	31.86%	16.81%	
PERIOD	Actual	6	15	30	81	64	44	224
11 STATS	%	2.68%	6.70%	13.39%	36.16%	28.57%	19.64%	
PERIOD	Actual	5	20	33	101	85	61	239
12 STATS	%	2.09%	8.37%	13.81%	42.26%	35.56%	25.52%	
PERIOD	Actual	0	0	1	8	5	3	21
13 STATS	%	0.00%	0.00%	4.76%	38.10%	23.81%	14.29%	
PERIOD	Actual	0	0	0	14	10	6	46
14 STATS	%	0.00%	0.00%	0.00%	30.43%	21.74%	13.04%	
PERIOD	Actual	2	8	27	70	50	31	179
15 STATS	%	1.12%	4.47%	15.08%	39.11%	27.93%	17.32%	
PERIOD	Actual	5	13	26	72	58	42	208
16 STATS	%	2.40%	6.25%	12.50%	34.62%	27.88%	20.19%	
PERIOD	Actual	2	10	23	58	49	29	197
17 STATS	%	1.02%	5.08%	11.68%	29.44%	24.87%	14.72%	

Note: This table summarizes the results of tests on individual continuously traded stocks' weekly returns. The results are broken down into period, and all periods which data was collected are included in the table. The first three result columns represent significant autocorrelation at the 5%, 1%, and 0.1% significance levels. The next three represent the existence of significant runs at the 90%, 95%, and 99% significance levels. The last column gives the total number of stocks with valid results from the specific period. The first row for each period gives the actual number of stocks with observed autocorrelation or runs at the specific significance level, while the second row gives the percentage that these stocks are of all stocks with valid results for a given data set.

The autocorrelation of residuals and runs tests repeated for weekly data had significantly different data, than for daily returns, as is shown in Table 16. The percentage of stocks that experience autocorrelation of residuals and runs significantly dropped. Over the whole data set (period 12), only 8.4% of continuously traded stocks were found to have autocorrelation of residuals at the 1%

significance level. The results for the runs test also exhibit a significant decline, with only 35.6% of stocks showing signs of runs at the 95% confidence level. These results show that only a small percentage of these stocks are weak form inefficient in their weekly price returns.

In the last period, the results indicate a more significant improvement in efficiency than was observed in the daily tests. In the last year of available data, only 5.1% experience autocorrelation at the 1% level, and 24.9% show signs of runs at the 95% level. This is a drop of 39% and 30% respectively from results from the whole data set. The weekly data shows this significant improvement in efficiency by the last time period. However, in the period groups tested for daily data, the trends and results are very similar. In general, none of the information distribution improvements cause immediate and significant efficiency changes. The data can be interpreted in the same manner as before, and does not represent any additional information not represented in the daily stock return results to require any more analysis.

The drastic improvement in weak-form efficiency visible in weekly-returns can be largely attributed to controlling for the 10% regulation in these tests. However, it is likely that the effect of the regulation is still captured to some degree in these results as well, since some pieces of information might require more than a week to be processed with this regulation in place. However, this is countered by an averaging effect in this data set, which does not pick up daily volatility in returns. This effect will reduce the observed serial correlation in prices, since prices are somewhat smoothed out. However, this effect will be especially minimal in the runs test, which is independent of return size. The significant change differences between the daily and weekly results cannot be attributed entirely to this effect. The percentage of stocks experiencing significant runs drops 59% in the weekly tests, which is not much different than the 65% drop in observed autocorrelation. This congruence suggests that the data is consistent with the notion of the 10% regulation largely causing the blatant inefficiency in daily results.

While the implications of the 10% price limit is quite clear from the results, another important conclusion can be drawn. Though these stocks seem more efficient in a weekly test, inefficiency still exists. This is especially true of the sequential price returns isolated by the runs test. Therefore, this is further evidence for an investor’s ability to actually profit on the WSE. While a trading strategy looking only to trade after a stock has moved almost 10% has a very high expected return, the chance of actually trading at this price level is very small, since only uninformed investors will be willing to trade. However, the weekly results suggest that serial correlation exists in returns even when prices do not hit the 10% limit. Though evidence of this serial correlation has weakened in the most recent tests, the effect persists. A possible trading strategy would be to focus on individual stocks, which exhibit clear serial correlation in their price movements.

4. Weak Form Efficiency in Auction Stocks

Though some very interesting conclusions were made from stocks trading in a continuous trading format, one would expect these effects to be magnified for smaller, less liquid stocks. These stocks have mostly traded in a call auction system since the beginning of continuous trading. The efficiency results for these small stocks are important in reflecting capital prices for smaller, and often newer firms. Furthermore, the results from these tests are more likely to show inefficiency and provide profit opportunities for informed investors.

Table 17. Tests for Auction Stocks (Daily Returns)

DAILY STATS FOR AUCTION STOCKS		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 1	Actual	0	1	3	2	2	0	9
	%	0.00%	11.11%	33.33%	22.22%	22.22%	0.00%	
PERIOD 2	Actual	3	6	10	15	14	4	16
	%	18.75%	37.50%	62.50%	93.75%	87.50%	25.00%	
PERIOD 3	Actual	12	14	16	8	8	2	25
	%	48.00%	56.00%	64.00%	32.00%	32.00%	8.00%	
PERIOD 4	Actual	0	0	3	6	2	2	33
	%	0.00%	0.00%	9.09%	18.18%	6.06%	6.06%	
PERIOD 5	Actual	8	16	27	47	43	33	80
	%	10.00%	20.00%	33.75%	58.75%	53.75%	41.25%	
PERIOD 6	Actual	15	180	192	54	51	41	98
	%	15.31%	18.37%	19.59%	55.10%	52.04%	41.84%	
PERIOD 7	Actual	13	24	33	41	39	29	81
	%	16.05%	29.63%	40.74%	50.62%	48.15%	35.80%	
PERIOD 8	Actual	20	31	43	49	46	37	99
	%	20.20%	31.31%	43.43%	49.49%	46.46%	37.37%	
PERIOD 9	Actual	47	75	102	213	208	192	242
	%	19.42%	30.99%	42.15%	88.02%	85.95%	79.34%	
PERIOD 10	Actual	42	69	101	210	205	188	242
	%	17.36%	28.51%	41.74%	86.78%	84.71%	77.69%	
PERIOD 11	Actual	58	69	82	124	122	118	133
	%	43.61%	51.88%	61.65%	93.23%	91.73%	88.72%	
PERIOD 12	Actual	77	101	139	225	219	203	252
	%	30.56%	40.08%	55.16%	89.29%	86.90%	80.56%	
PERIOD 13	Actual	9	19	29	60	54	44	91
	%	9.89%	20.88%	31.87%	65.93%	59.34%	48.35%	
PERIOD 14	Actual	5	18	39	106	90	31	149
	%	3.36%	12.08%	26.17%	71.14%	60.40%	20.81%	
PERIOD 15	Actual	61	95	126	216	207	188	241
	%	25.31%	39.42%	52.28%	89.63%	85.89%	78.01%	
PERIOD 16	Actual	36	41	51	95	95	95	96
	%	37.50%	42.71%	53.13%	98.96%	98.96%	98.96%	
PERIOD 17	Actual	12	20	28	66	66	65	68
	%	17.65%	29.41%	41.18%	97.06%	97.06%	95.59%	

Note: This table summarizes the results of tests on individual auction traded stocks' daily returns. The results are broken down into periods, and all periods in which data was collected are included in the table. The first three result columns represent significant autocorrelation at the 5%, 1%, and 0.1% significance levels. The next three represent the existence of significant runs at the 90%, 95%, and 99% significance levels. The last column gives the total number of stocks with valid results from the specific period. The first row for each period gives the actual number of stocks with observed autocorrelation or runs at the specific significance level, while the second row gives the percentage that these stocks are of all stocks with valid results for a given data set.

Daily Return Results

Over the course of the whole data set, as described by the results from period 12 in Table 17, the runs test statistics are not much different than those for continuously traded stocks. At the 95% confidence level, 85.9% of stock had significant runs in comparison to 87.0% for continuously traded stocks. However, the autocorrelation results do show significant differences. 40.1% of auction stock were observed to have autocorrelation of residual at the 1% significance level in comparison to 24.3% for continuous stocks. This represents a significant difference in one's prediction ability from past prices. The similarity in the runs test results suggests similar degrees of runs. However, the autocorrelation results represent the ability to better predict the size of price moves in these auction stocks. This feature would prove to be important to an investor attempting to profit from a weak form inefficiency because he will be able to make much more accurate predictions of the size of future movements, instead of simple runs.

The higher percentage of inefficiency is again visible in period 17, representing the last year of data. However, in this period, the autocorrelation statistics converge, while the runs results are much more prominent in auction stocks. This suggests that specific predictive ability based on past prices has declined. However, statistically significant runs are very common, 95.9% at the 99% significance level. Thus, these stocks continue to move in sequential trends more often than would be expected. This information can be used to develop a trading strategy taking advantage of runs in these small, auction traded stocks.

Weekly Return Results

The weak-form efficiency tests of auction prices are extended to weekly stock prices, as was done for continuously traded stocks. These results will be especially important for this segment of stocks. The results for continuously traded stocks strongly suggest that the 10% price limit is a very significant cause of weak form inefficiency. When this effect is discounted, the data exhibits results much closer to efficiency. The auction stocks, like continuously traded ones, would be difficult to trade if a stock should move more than 10%. Therefore, these price moves will provide very little liquidity, and it is necessary to evaluate if investors can still profit when the 10% regulation is made inconsequential, as in the weekly data. Since it is hypothesized that the auction system is more inefficient than the continuous segment, the ability to profit from serial correlation in these stocks is most important to investors.

Table 18. Tests for Auction Stocks (Weekly Returns)

WEEKLY STATS FOR AUCTION		Significant AC (0.1%):	Significant AC (1%):	Significant AC (5%):	Runs (90%):	Runs (95%):	Runs (99%):	Total:
PERIOD 1	Actual	0	1	3	2	2	0	9
	%	0.00%	11.11%	33.33%	22.22%	22.22%	0.00%	
PERIOD 2	Actual	0	1	2	5	5	0	16
	%	0.00%	6.25%	12.50%	31.25%	31.25%	0.00%	
PERIOD 3	Actual	0	1	1	3	1	0	25
	%	0.00%	4.00%	4.00%	12.00%	4.00%	0.00%	
PERIOD 4	Actual	0	0	0	8	3	2	33
	%	0.00%	0.00%	0.00%	24.24%	9.09%	6.06%	
PERIOD 5	Actual	0	0	7	8	5	2	80
	%	0.00%	0.00%	8.75%	10.00%	6.25%	2.50%	
PERIOD 6	Actual	0	3	8	13	9	6	98
	%	0.00%	3.06%	8.16%	13.27%	9.18%	6.12%	
PERIOD 7	Actual	1	1	6	10	6	1	81
	%	1.23%	1.23%	7.41%	12.35%	7.41%	1.23%	
PERIOD 8	Actual	1	4	7	17	11	7	99
	%	1.01%	4.04%	7.07%	17.17%	11.11%	7.07%	
PERIOD 9	Actual	4	11	34	108	79	42	242
	%	1.65%	4.55%	14.05%	44.63%	32.64%	17.36%	
PERIOD 10	Actual	4	13	33	104	79	36	242
	%	1.65%	5.37%	13.64%	42.98%	32.64%	14.88%	
PERIOD 11	Actual	11	23	40	99	88	71	133
	%	8.27%	17.29%	30.08%	74.44%	66.17%	53.38%	
PERIOD 12	Actual	21	28	40	144	123	87	252
	%	8.33%	11.11%	15.87%	57.14%	48.81%	34.52%	
PERIOD 13	Actual	0	2	7	14	7	4	91
	%	0.00%	2.20%	7.69%	15.38%	7.69%	4.40%	
PERIOD 14	Actual	0	1	12	41	24	5	147
	%	0.00%	0.68%	8.16%	27.89%	16.33%	3.40%	
PERIOD 15	Actual	7	21	40	122	94	55	241
	%	2.90%	8.71%	16.60%	50.62%	39.00%	22.82%	
PERIOD 16	Actual	6	17	25	80	76	68	96
	%	6.25%	17.71%	26.04%	83.33%	79.17%	70.83%	
PERIOD 17	Actual	1	4	10	44	43	40	68
	%	1.47%	5.88%	14.71%	64.71%	63.24%	58.82%	

Note: This table summarizes the results of tests on individual auction traded stocks' weekly returns. See the note from Table 17 for a description of the format.

Weekly results again show a significant decline in the percentage of stocks with significant runs or autocorrelation, as seen in Table 18. While the 45% drop in the percentage of significant run observation for the entire data period is in line with the continuous stock results, the autocorrelation observations are even more significantly affected. The percent of auction stocks experiencing autocorrelation of residuals is nearly 75% less for weekly data than daily data. This again suggests the prominence the 10% price limit has in the weak- form inefficiency observed in these stocks. The significant difference between daily and weekly results suggests that the 10% price limit is more often applied to these stocks. This is a reasonable conclusion since these stocks are less liquid, and it is probably difficult to balance all the orders when an order of bigger size comes into play. The inefficient results of the 10% regulation are very clear in these stocks. While it certainly minimizes volatility, it also prevents free market action and the quick execution of orders.

The same observation above holds for period 17, representing the last year of complete data. As noted above, the smaller decline in significant runs suggests that the market is still not efficient when the 10% regulation is not a factor. In period 17, 63% of auction stocks experienced statistically significant runs on a weekly price change basis. This result suggests that the market remains weak- form inefficient till the present. Furthermore, this suggests profitable trading strategies can continue to outperform the market, especially in less liquid market segments.

Lastly, the higher degree of efficiency in continuously traded stocks over auction stocks credits the WARSET electronic trading system for encouraging efficiency. While bought segments of stocks are seen to have a small and similar percentage of significant autocorrelation, 63.2% of the auction stocks have 95%

significance level runs in comparison to 24.9% for continuously traded ones. This supports the WARS ET conclusions, and is consistent with the hypothesis that smaller, lower volume stocks present the best opportunities for profit.

An important point to note is that discovering inefficiencies in the market is to the benefit of the exchange and Polish economy. As inefficiencies are exposed, investors will attempt to take advantage of them for profit. However, in the meantime they also improve the price information of the market by reducing the profit margin. Eventually, these opportunities for profit disappear as they become general knowledge. Though it might seem counterintuitive, it is actually to the benefit of the exchange for investors to expose, and take advantage of, inefficiencies. In the long run, the inefficiencies will disappear and the market will be an effective pricing mechanism for capital that reduces risk for the parties involved. The market can assist this process by providing full and candid information. The amount of information made available by the WSE, relative to other emerging markets, implies that this is being largely implemented.

VIII. Final Conclusions

In this study, I focused on 4 questions concerning efficiency on the Warsaw Stock Exchange. To answer these questions, a number of tests were conducted that provided answers to one or more of these answers. I conclude by looking at each one of the original questions and how they were answered.

The first and primary goal of this paper was to analyze the weak form efficiency of the WSE. The index analysis results showed the index as generally inefficient. However, a very interesting result arose from this test. It was very clear from the WIG and WIG20 results that the implementation of the WARSET system had a profound impact on the efficiency of the market. However, this observation was not so clear in the individual stock tests. These individual stocks tests showed a market that remained relatively inefficient throughout its history. The general conclusions I was able to make are that the WSE has made steps forward in proving the integrity of the exchange. However, the individual stock results paint a more bleak picture, where progress has been slow and inconsistent. This was supported by the January effect results: a January effect seems to exist till today.

However, the majority of the WSE's inefficiency can be blamed on the WSE's 10% price change limit. This regulation pretty much guarantees serial correlation in price returns. It also required an extended weak form efficiency study to decipher if the WSE allows opportunities for investors to make a profit. The weak form tests of weekly data made the sever effect of the regulation clear. These tests also provided evidence on significant runs in individual stocks after controlling for regulation. The tests of the January effect also confirmed another profit opportunity. The WSE's January effect allows investors to make systematic profits from significant seasonal trends. Furthermore, by focusing on small, illiquid stocks, investors seem to be more likely to find inefficiencies. The strategies proposed here are relatively well known and simple, but they indicate the existence of other such strategies, because prices can be calculated based on past prices alone. This observation is important to any investor, and encourages him to implement these simple strategies and seek out others.

To compare the WSE to other emerging markets one needs to focus on index results because these are generally the only ones available for other exchanges. The WSE seems to have significantly improved in efficiency when studied by its indices, and therefore places itself in the more advanced group of emerging markets. However, it does not compare to developed markets like the US, which have not seen a valid January effect for 30 years. Nonetheless, for a thirteen year old market, the WSE has grown quickly and has made some important headway into becoming an efficient exchange.

The most important of these advances seems to have been the introduction of the WARSET system, which instantaneously improved its overall market efficiency. The other improvements in information distribution seems to have extended effects that take a while to implement. Nonetheless, the importance of a fast access electronic system to the WSE's improvement in efficiency should be a model for other emerging and transitional exchanges.

Another important lesson for capital markets, including the WSE, is the negative impact of trading regulations that place limits on the free market. Though such strict rules might be seen as a necessary evil for a short period of time to maintain rational markets, they should be abolished at the first opportunity. The regulation is the most important factor in keeping the stocks of the exchange weak form efficient, and therefore the exchange cannot act as an effective price information mechanism for the economy. Though regulations are likely necessary to prevent sever panics, regulations as strict and hindering as Poland's are unnecessary.

In this paper, I was able to successfully answer these questions, with meaningful and relatively consistent results. A direction for future research is to expand this study to include semi- strong form efficiency tests. However, the available data prevents such a study, and the market and fundamental data would have to be collected privately. This however could provide investors with more effective trading strategies for profit on the WSE. The expansion of efficiency tests to the WSE's bond and derivative markets are also likely to present opportunities in some of these more complex products.

Such attempts and studies will lead the exchange to higher degrees of efficiency. However, the exchange should also take proactive steps by getting rid of regulation, and providing complete and detailed information to investors. Nonetheless, the WSE has taken some important steps to providing market participants with better information relative to other markets of similar size and history. With continuing progress, the WSE can become priceless tool for the Polish economy to attract investment and regulate its capital market.

X. Works Cited

Abraham, Abraham, Fazal J. Seyyed and Sulaiman A. Alsakran. "Testing the Random Walk Behavior and Efficiency of the Gulf Stock Markets." Financial Review 37.3 : 469-480.

Brealey, Richard A., and Stewart C. Myers. Principles of Corporate Finance. Ed. Sarah Ebel. 7th ed. New York: McGraw-Hill Higher Education, 2003.

Cooper, Richard V. L. "Efficient Capital Markets and the Quantity Theory of Money." .

Cuthbertson, Keith, Simon Hayes and Dirk Nitzsche. "The Behaviour of UK Stock Prices and Returns: Is the Market Efficient?" Economic Journal 107.443 : 986-1008.

El-Erian, Mohamed A., and Manhoman Kumar. "Emerging equity markets in Middle Eastern countries." International Monetary Fund Staff Papers 42.2 (1995): 313.

Fama, Eugene F. "Efficient Capital Markets: A Review of Theory and Empirical Work." Journal of Finance 25.2 : 383-417.

---"Efficient Capital Markets: II." Journal of Finance 46.5 : 1575-1617.

General Information on the Polish Economy. Poland Ministry of Foreign Affairs. 5/1/2004. <http://www.poland.gov.pl/?page=1050000001>.

Gu, Anthony Y. "The Declining January Effect: Evidences from the U.S. Equity Markets." Quarterly Review of Economics and Finance 43.2 : 395-404.

Gujarati, Damodar N. Basic Econometrics. Ed. Lucille Sutton. 4th ed. New York: McGraw Hill Higher Education, 2003.

Hanousek, Jan, and Richard Podpiera. "Informed Trading and the Bid-Ask Spread: Evidence from an Emerging Market." Journal of Comparative Economics 31.2 : 275-296.

Henke, Harald. Tax Loss Selling and Window Dressing: An Investigation of the January Effect in Poland. Frankfurt (Oder): Europe-Universitat Viadrina, 2003.

---When Continuous Trading Becomes Continuous. Frankfurt (Oder): Europe-Universitat Viadrina, 2004.

Jones, Charles P., Douglas K. Pearce and Jack W. Wilson. "Can Tax-Loss Selling Explain the January Effect? A Note." The Journal of Finance 42.2 (1987): 453.

LeRoy, Stephen F. "Efficient Capital Markets: Comment." Journal of Finance 31.1 : 139-141.

Magnusson, Magnus A., and Bruce Wydick. "How Efficient Are Africa's Emerging Stock Markets?" Journal of Development Studies 38.4 : 141-156.

Maloney, Michael T., and J. H. Mulherin. "The Complexity of Price Discovery in an Efficient Market: The Stock Market Reaction to the Challenger Crash." Journal of Corporate Finance: Contracting, Governance and Organization 9.4 : 453-479.

Mandilaras, Alex. EC 679 Lecture Notes V EMH. 12/19/2003. 5/1 2004. <http://www.econ.surrey.ac.uk/amandilaras/lec5.pdf>.

Poland, Polish Political Geography 2003. Columbia University Press. 5/1/2004. <http://reference.allrefer.com/encyclopedia/P/Poland-economy.html>.

The Warsaw Stock Exchange Website 2003. 5/1/04. <http://www.wse.com.pl>.

Wheeler, Fred, et al. "The efficiency of the Warsaw Stock Exchange: the first few years 1991-1996." The Poznan University of Economics Review 2.2 (2002): 37.

Yahoo Finance 2004. Yahoo Inc. 5/1/2004. <http://finance.yahoo.com/>.

Zalewska-Mitura, Anna, and Stephen G. Hall. "Do Market Participants Learn? The Case of the Budapest Stock Exchange." Economics of Planning 33.1-2 : 3-18.