INDUSTRY PORTFOLIOS, INFORMATION DIFFUSION AND THE PREDICTABILITY OF STOCK RETURNS IN KENYA

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Proposal contains no material previously published or written by another person except where due reference is made in the Research Proposal itself.

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List of Abbreviations

EMH Efficient Market Hypothesis

NSE Nairobi Securities Exchange

CBK Central Bank of Kenya

CPI Consumer Price Index

KNBS Kenya National Bureau of Statistics

GMM Generalized Method of Moments

AB Arellano-Bond

GLS Generalized Least Squares

ABSTRACT

This paper tests the hypothesis that stock return predictability exists in the Kenyan market. In particular, it investigates whether in the presence of gradual information diffusion, which is as a result of investors' limited information processing ability, lagged industry portfolios excess returns are able to predict the NSE 20 stock market index excess returns, which serves as a proxy for the entire stock market. Five market capitalization weighted industry portfolios, namely Agriculture, Financial Services, Commercial and Services, Manufacturing and Energy and Transport are constructed using stock returns from the year 2005 to 2015. The lagged industry portfolio expected returns, the market expected returns and the industry portfolio residuals (both lagged and for the current period) are fitted into an information diffusion model and thereafter the industry predictability and information diffusion coefficients are estimated using the Arellano-Bond GMM Estimator. The findings suggest that there is no causal relationship between the industries and the stock market and no gradual information diffusion. This implies that for the Kenyan stock market, there is no stock return predictability when the analysis is performed using the industry and wider stock market approach.

JEL classification: G12, G14

Key words: gradual information diffusion, stock return predictability, Arellano Bond GMM Estimator

1 INTRODUCTION

1.1 Background to the study

Several existing studies on stock return predictability have been conducted from the industry portfolios perspective which takes into account the relationships between the industries under consideration. This industry analysis has been done using three main approaches. The first approach analyses the industry portfolios' returns ability to predict other industry portfolio returns due to the fact that the industries either have a supplier- customer relationship or are trading partners. See for instance -Cohen & Frazzini (2008) and Aobdia, Caskey & Ozel (2014). The second approach analyses the ability of firms within an industry to predict each other's returns, also referred to as the lead-lag effect. One such study is that of Hou (2007). The final approach, which is also the approach that is adopted in this study, focuses on the ability of lagged industry portfolio returns to predict the wider stock market by predicting the stock market index returns and has been studied by Hong, Torous & Valkanov (2007), Tse (2015) among others.

Fama (1970) reviews predictability studies for the US and European markets between 1934 and 1969 and concludes that markets are efficient for the most part and stock returns follow a random walk hence there can be no predictability. Following Fama's work alternative[1] theories to the Efficient Market Hypothesis (EMH) have been developed to explain how stock return predictability and market efficiency can exist simultaneously. The theories include, the effects of thin trading; market frictions such as information costs; transaction costs and non-synchronous trading; investor behavioral biases; information from and the effect of macroeconomic variables on the stock market and the gradual diffusion of information hypothesis-the grounding hypothesis in this study as well as the preceding studies (see for instance Hong et al. (2007), Cohen& Frazzini (2008) and Tse (2015)) that have analyzed stock return predictability from the industry portfolio perspective.

The gradual diffusion of information hypothesis argues that investors participate in a limited number of markets due to their limited ability to process information, a fact that has been supported

[1] These alternative theories offer independent explanations of stock return predictability and do not view it as a consequence of lack of market efficiency.

by studies on investor psychology such as Sims (2003), DellaVigna (2009) and (Loh, 2010). Supporters of this hypothesis further argue that the fact that there is specialization of traders and money market managers in certain asset classes or markets is in itself evidence of the investors' limited abilities to process information. Therefore, one of the consequences of this limited information processing ability (or the lack of access to the information entirely) is that the information from other markets that the investor does not specialize in reaches them only with a lag, where the length of the lag varies with the market under consideration. It has also been argued by researchers such as Hong, Lim & Stein (2000) that the gradual diffusion of information is more prominent when the information is bad news given that managers are more unwilling to release negative information to the public. However, it should be noted that while several researchers have found evidence in support of the gradual diffusion of information hypothesis, there exists differences in opinion regarding whether the stock return predictability is only exhibited in the short run, as found by Lo & Mackinlay (1990) and Bekaert (2007), or also in the long run.

As with most hypotheses/ theories in finance, there are researchers who have opposed the validity of the gradual diffusion of information hypothesis as well as the other alternative explanations of stock return predictability. In particular, supporters of the EMH have put forth arguments that have sought to discredit these alternative explanations, thereby reaffirming that there can be no stock return predictability if markets are found to be efficient given that the stock prices follow a random walk. One popular argument is that the cause of the predictability is the choice of asset pricing model used. This is because not only do behavioral models work well explaining the anomalies that they were designed to analyze and explain, but also the anomalies disappear once a change is made to the method of estimation, the sampling period or out-of-sample data is used instead, Fama (1998). Malkiel (2003) also argues that financial ratios such as dividend yields and other macroeconomic variables' ability to predict the stock market may just be a reflection of the stock market readjusting to the prevailing market conditions and not an indication of the underlying market inefficiency. The last argument is that market efficiency and stock return predictability are not necessarily mutually exclusive; markets can be efficient and at the same time exhibit stock return predictability since excess stock return predictability on its own does not necessarily imply market inefficiency (see Pesaran &Timmerman (1995),Sagi & Seasholes (2007) and Liu & Zhang (2008) and most recently Pesaran (2010) and Tuyon & Ahmad (2016)).

While the US in particular and other international markets have been comprehensively studied, this is not the case for the African stock markets. Very few, if any, purely African centered studies on stock return predictability exist. Furthermore, the primary focus of the African studies that exist on stock return predictability is testing market efficiency. Conclusions made on the existence of stock return predictability are based on the premise that markets are inefficient and not as a result of the alternative explanations such as the gradual diffusion of information. For instance, Smith & Dyakova (2014) find that Kenya is one of the least informationally efficient markets in Africa. They subsequently conclude that Kenya therefore demonstrates high stock return predictability. The current study aims at not only analyzing stock return predictability of the Kenyan stock market by testing the ability of industry portfolios to predict the stock market, but also by analyzing the stock return predictability as a result of the gradual diffusion of information.

1.2 Motivation of the study

In the purely African markets studies that have been conducted, stock return predictability goes hand in hand with market inefficiency. However, in the case of the Kenyan stock market there are conflicting results as to whether or not the market is efficient and therefore does not demonstrate stock return predictability. For instance, a recent study on eight African markets by Smith & Dyakova (2014) tests the martingale hypothesis using the daily stock indices return data from 1998 to 2011 that have been corrected for thin trading-one of the alternative explanations to the EMH. They also employ the use of a fixed-length rolling window so as to capture short-horizon predictability and facilitate ranking of the markets based on the observed predictability. Their findings corroborate those of Jefferis & Smith (2005) and Mlambo & Biekpe (2007) who conclude that the Kenyan stock market is one of the most inefficient and thus demonstrates stock return predictability. However, their findings also add to the conflicting results on the Kenyan market's efficiency, and hence its stock return predictability, given than previous studies such as those by Dickinson & Muragu (1994) and Appiah-Kusi & Menyah (2003) find that the Kenyan market is weak form efficient.

It is on the auspices of these findings that the study seeks to test stock return predictability as a result of the gradual diffusion of information. In so doing, the study contributes unique knowledge on stock return predictability in the Kenyan stock market. It also contributes to the development of knowledge on the gradual diffusion of information as an alternative explanation of stock return predictability.

1.3 Statement of the problem

Recent findings of the evidence of return predictability in certain markets have led to the development of alternative explanations to the EMH which include the effects of thin trading, gradual information diffusion, among others. In spite of the arguments against these hypotheses (see Fama (1998)), some, such as the gradual diffusion of information have continued to gain credibility.

The gradual diffusion of information hypothesis has been supported by authors such as Hong & Stein (1999), Boguth, Carlson, Fisher & Simutin (2016), among others. Their studies seek not only to establish the validity of this hypothesis but also to develop models that can capture the gradual diffusion of information. While they have been able to achieve their objectives, their studies have been limited to the United States and the European markets (developed markets). Therefore, there is an evident gap in the knowledge relating to the frontier markets such as Kenya. Most predictability studies in Kenya follow from tests of market efficiency; if the market is found to be inefficient, then there is stock return predictability. Despite recent findings that stock market predictability isn’t necessarily a consequence of market inefficiency, other plausible explanations such as gradual information diffusion have received no attention. Therefore, this study proposes to analyze stock return predictability as evidenced by the relationship between the selected industries and the stock market, while incorporating the effects of gradual information diffusion.

1.4 Research objective

The objective of this study is:

To determine if industry portfolios’ excess returns can predict the stock market’s excess returns amidst gradual information diffusion.

1.5 Research questions

The research question that will guide this study is:

Do industry portfolios’ excess returns predict the stock market’s excess returns in the presence of gradual information diffusion?

1.6 Scope of the study

This study analyzes stock return predictability from the broader perspective of industry portfolio predictability. In particular, the focus of this study is the ability of industry portfolios to predict the stock market index which serves as a proxy for the broader stock market. This study will focus on the Kenyan stock market from the year 2005 to 2015.The industry portfolios constructed will be on the basis of the industry categorization provided by the Nairobi Securities Exchange.

1.7 Justification of the study

The gradual diffusion of information hypothesis has gained significant interest in finance especially during the 21st Century given its link to behavioral finance which has also become increasingly popular. This has resulted in its growing importance as an alternative explanation to the EMH in explaining stock return predictability. Kenya as a frontier market has recently gained increased interest from foreign investors. Increasing financial literacy of the Kenyan citizens has also led to increased interest in the stock market by the local investors. However, in order to increase investor participation and confidence, one of the key requirements is an understanding of how the market works and the behaviour of stock prices. This study hopes to contribute to investors' knowledge of the market by not only contributing to the literature on the analysis of the market, but also by hopefully providing a reasonable explanation of the observed behaviour of stock prices, taking into account the effects of investor behavior on the observed stock prices.

2 LITERATURE REVIEW

2.1 Introduction

There are several studies that have been done on predictability from various perspectives and using different model specifications. In this section we review literature on stock return predictability from the wider industry portfolio perspective. The subsections highlight the different interrelationships between the industry portfolios. We also review the literature on the gradual diffusion of information hypothesis.

2.2 Stock market predictability

The studies reviewed in this section all anchored their research on the gradual diffusion of information hypothesis. While the researchers had in common this fundamental theory guiding their study, they differed in their approach to studying stock return predictability.

2.2.1 Predictability between the industries and the markets

Hong, Torous and Valkanov (2007) study this form of predictability for the US market and 8 other developed markets including Germany and Japan. With the exception of Japan, they find that the industries can predict the stock market returns and in the case of the US market, a total of 14 industries are able to predict the broad stock market index and others such as financial services can do so by up to 2 months. Additionally, after specifying a model that includes indicators of economic activity such as industrial production growth and market predictors such as inflation and market dividend yield similar to those considered by Pesaran &Timmerman (1995) they argue that an industry's ability to forecast the market is strongly positively correlated to the its ability to predict market fundamentals. However, in a more recent study done by Tse (2015) who reexamines the findings of Hong et al. (2007), he argues that by using a more robust data set that includes a longer time period and more industry portfolios, fewer industries are able to predict the stock market and those that do, do so with less statistical significance. Furthermore, he argues that the direction of the predictive relationship is in fact the other way around; that the stock market predicts the industries and outperforms the industries in predicting macroeconomic factors.

This difference in results relating to whether or not industries can predict the stock market and if indeed that is the direction of the causal relationship also highlights the different underlying economic theories as to why the observed is the case. Are markets efficient or is information reflected in the stock market with a lag due to limited investor market participation which then results in the gradual diffusion of information? Nonetheless, the findings on stock return predictability by Hong et al. (2007) may well be intuitive given the existing market frictions and proven investor behavioral biases.

2.2.2 Across industry predictability- inter-industry effects

Several authors have studied the inter-industry effects particularly for the US market. However, their studies differ primarily due to their definitions of industries and the inter-industry effect they seek to establish exists. For instance, Menzly & Ozbas (2006), (2010) focus on cross-industry momentum among related upstream (supplier) or downstream (customer) industries. They postulate that the returns of upstream and downstream industry portfolios could predict the returns of the industry in which they belong. Cohen and Frazzini (2008) analyze individual firms that are economically linked, that is, have an explicit supplier-customer relationship[2]. They seek to prove that customer firms are able to predict the monthly returns of the supplier firms that they are linked to due to investor inattention[3]. Aobdia, Caskey & Ozel (2014) analyze the cross-predictability between industries that are trading partners and propose that any predictability would be due to inter-industry trade flows, for this is the channel through which information and economic shocks flow between the existing industries. Lastly, Hou (2007) studies the inter-industry lead-lag effect by analyzing what is broadly categorized as either a big or a small firm.

As a result of their different focus points, their findings vary and as such offer a variety of explanations for the inter-industry predictability. Interestingly, given that the studies are conducted in different years, the researchers acknowledge the work done by their predecessors and some even control for their predecessors' findings and subsequently conclude that their current findings still hold. For example, Cohen et al. (2008) find that customer firms are able to predict the monthly returns of supplier firms but only if the two are linked and they refer to this predictability as 'customer momentum'. Furthermore, even after controlling for alternative explanations for predictability such as cross industry momentum (lagged customer and supplier returns' ability to predict the monthly excess returns of their respective industries over short time horizons) as proposed by Menzly & Ozbas (2006) they find that the magnitude and significance of the customer

[2] In this case, the customer accounts for 10% or more of the supplier's total sales.
[3] The investor pays little or no attention to the fact that these links exist. This inattention will then result in the supplier's returns adjusting to the information about the customer firm with a lag.

momentum remains unchanged . Also, both Menzly et al. (2006), (2010) and Cohen et al. (2008) find that abnormal returns can be made by buying or selling stocks of the supplier firm or industry following news about their respective customers or customers and supplier firms respectively. On the other hand, Aobdia et al. (2014), whose study focuses on the broader trade linkages between firms, find that central industries[4]-industries that served as hubs- are able to predict the returns of their trade partners, but the single industries that were non-central and only served as trading partners in the network were not able to predict the returns of central industries.

In contrast to these findings that inter-industry predictive effects exist, Hou (2007) finds that the predictive power of big firms that are outside the industry is dominated by the big firms within the industry. In fact, he argues that once he controls for the big firms within the industry, the big external firms have no predictive power which leads him to conclude that the inter industry effects are insignificant. Therefore, in spite of these findings being arrived at independently, it is possible that all of the observed interrelationships are linked in one way or another. Aobdia et al. (2014) state that their study is different because they study trade linkages. However, they do not separate the specific customer-supplier predictive power observed by Menzly et al. (2006), (2010) and Cohen et al. (2008) from the broader central industry predictive power. Furthermore, the conclusion drawn by Hou (2007) may not be fully justified given that within the big and small firm categories some industries may have predictive effects and others do not and this may reduce the overall effect to an insignificant amount.

2.2.3 Intra-industry predictability

Unlike the other researchers previously discussed in this paper, Hou (2007) takes a micro approach in his study. While he tests for inter-industry lead-lag effects, his primary objective is the intra-industry effect. His study builds on the that of Lo & Mackinlay (1990) who find that cross effects (positive cross autocorrelation among stock returns) which account for more than 50% of contrarian profits are more distinctive over shorter time horizons especially for portfolios that are sorted according to size (large capitalization stock portfolios and small capitalization stock portfolios). They however do not group the stocks into their specific industry portfolios.

[4] The stronger the trade ties an industry had with other industries that had their own equally strong ties, the higher its centrality. For example real estate and wholesale trade were found to be some of the most central industries.

It is on this shortcoming that Hou (2007) builds his study for he not only groups the US stocks based on size, but also on the basis of the industry to which they belong. He postulates that the size related lead-lag effect identified by Lo et al. (1990) is stronger than not only the inter-industry effect but also than the effect between the industries and the stock market. From his analysis he finds that in addition to the big firms[5] being able to predict the returns of small firms within the same industry, the lagged small firm returns are unable to predict current big firm returns since the large firms' stock prices react faster to new information. Interestingly, he also finds that this predictive power is even stronger when the information is bad news since bad news travels slower than good news, a finding that corroborates those of Hong, Lim & Stein (2000).

Contrary to Lo et al. (1990) who argue that the lead-lag effect could be as a result of thin trading and Hong et al. (2007) who attribute the gradual diffusion of information to limited investor participation, Hou (2007) argues that the lead-lag effect is as a result of the slow diffusion of information which arises due to market frictions and institutional constraints such as legal restrictions. Additionally, his findings also indicate that the lead lag effect is weaker for the second half of the sampling period which is consistent with the current need for increased disclosure by firms resulting in reduced market friction. He also identifies other predictability drivers such as analyst coverage (also found to result in a lead-lag effect by Brennan, Jegadeesh & Swaminathan (1993)), institutional ownership (first identified by Badrinath, Kale & Noe (1995)), trading volume and market share. However, he tests each driver's predictive power in isolation and does not show how much of the overall observed predictability is attributable to each.

2.3 Gradual information diffusion

One of the pioneer behavioral models that captures the gradual diffusion of information was designed by Hong & Stein (1999). The model assumes that there are two types of investors (news watchers and momentum traders) who are boundedly rational, meaning that they have limitations in their ability to process information. They argue that initially, stock prices underreact due to the fact that private information diffuses gradually to all investors (in this case the news watchers), This is primarily because the investors are unable to perform the rational expectations trick, that is, extract each other's information from the prevailing stock prices. The underreaction is later

[5] He arrives at his size classifications by sorting the firms into bottom, middle and top and then equally weights the bottom and top so as to prevent bias towards the top, which would be the case if he used value weighting.

followed by a correction which is due to momentum traders trying to exploit the existing mispricing. Informed by the arguments put forth by (Fama, Market Efficiency, Long term Returns and Behavioral Finance, 1998), Hong, Lim & Stein (2000) test a different hypothesis using the initial model. They postulate that the gradual diffusion of information that is observed using the initial model of Hong et al. (1999) should be greater for smaller firms given that they have lower analyst coverage and higher information costs. This time, they use residual analyst coverage as a proxy for information diffusion where the coverage is equivalent to the number of analysts who provide information within a 1-year period. The fact that the results generated are strongly consistent with their hypothesis leads them to assert the validity of the gradual diffusion of information hypothesis and the model of (1999). They also find that information diffuses at the slower rate when the information is bad news. The studies in subsequent years of Doukas & McKnight (2005)[6] and Yalcin (2008)[7] test the model of information diffusion introduced by Hong & Stein (1999) for 13 European countries and the US market respectively and their findings are consistent with the initial behavioral model results. Yalcin (2008) also finds that the gradual diffusion of information is more prominent for glamour stocks as opposed to value stocks.

On the other hand, similar to Hong et al. (2007), Rapach, Strauss & Zhou (2013) use GMM to estimate a news diffusion model which they use to test if the US stock returns are able to predict non-US returns such as those of Japan and Canada. They find that lagged US stock returns are able to predict non-US returns but the reverse relationship does not hold. They conclude that their findings, in spite of the different model specification, support the gradual diffusion of information explanation for stock return predictability.

A unique model for slow information diffusion is developed by Boguth, Carlson, Fisher & Simutin (2016). Unlike preceding authors, their model accounts for the fact that information diffuses at different speeds for different stocks-"heterogeneous information diffusion'. Furthermore, they differentiate their model by using the ratio of the lagged factor loadings estimated from the regressions, to the total sum of all loadings as a proxy for slow information diffusion. While the models specifications and the proxies used to capture gradual information diffusion may differ

[6] They use an out of sample data set so as to prevent their findings from being dismissed by the arguments put forth by (Fama, Market Efficiency, Long term Returns and Behavioral Finance, 1998).

[7] In addition to using the residual analyst coverage as a proxy for the gradual diffusion of information, they condition the residuals to firm size. They also use ex-post returns as a proxy for expected returns.

across the authors, it is observed that they all incorporate the aspect of lagged returns (whether of the market or the stocks) in the model specifications as part of the constraints to capture the gradual diffusion of information.

3 METHODOLOGY

This is a quantitative study that seeks to establish if industry portfolios excess returns are able to predict excess returns of the stock market. The industry portfolio returns are computed as the market-capitalization weighted return of the constituent securities returns. Once the number of lags are estimated, the lagged variables are fitted into a dynamic panel model and thereafter the industry predictability coefficients are estimated using the Arellano-Bond GMM Estimator. A Granger causality test is also performed to confirm the direction of the causal relationship between the industries and the market.

3.1 Data types and sources

The industry portfolios are constructed on the basis of the industry categories as provided by the NSE. There are currently 10 industry categories and they include: Agricultural, Automobiles and Accessories, Banking, Commercial and Services, Construction and Allied, Energy, Insurance, Investments, Manufacturing and Allied and Telecommunication.

Monthly stock price data, the market index data and the market capitalization data will be obtained from the NSE. Given that the final returns used in the regression model are the excess returns, the 91-day T-bill rate will serve as the proxy for the risk free rate. This is because given that it is the shortest term government security available, the rate most accurately represents changes in the risk free rates in the economy. These historical rates will be obtained from the CBK database.

Data on inflation which is measured as the growth rate of the Consumer Price Index shall be obtained from the CBK database. The computations by the CBK are done using monthly CPI Index data from the KNBS database.

3.2 Population and sampling

The sampling period of this study will be from the year 2005 to 2015. The NSE 20 Index is used as the proxy for the stock market for its returns span the entire sampling period. The NSE 20 Index is a value weighted index of the 20 best performing listed companies which are selected on the basis of 40% market capitalization, 20% number of deals, 30% shares traded and 10% turnover.

The criteria for security selection are: the security must have been listed by 2005 and it should not have been suspended from trading by the NSE at any point in time during the sampling period. Thinly traded securities are also not considered given that they would have missing data.

Therefore, following the stock selection process, industries with similar characteristics are aggregated to form a wider industry category so as to prevent the creation of portfolios with less than four stocks. The final industry portfolios and their respective securities are listed in the table below.

Table 1: Industry Portfolios and their constituent securities

Industry	**Securities**
Agriculture	Eaagads Ltd, Kapchorua Tea Company Ltd, Limuru Tea Company Ltd, Sasini Ltd, Williamson Tea Kenya Ltd
Financial Services	Barclays Bank Ltd, Kenya Commercial Bank Ltd, Standard Chartered Bank Ltd, Diamond Trust Bank Kenya Ltd, Housing Finance Corporation Kenya Ltd, National Bank of Kenya Ltd, CFC Stanbic Holdings Ltd , I&M Bank Holdings Ltd(Previously City Trust Ltd), NIC Bank Ltd, Jubilee Holdings Ltd, Pan Africa Insurance Holdings Ltd, Olympia Capital Holdings Ltd, Centum Investments Company Ltd
Commercial and Services	Express Kenya Ltd, Kenya Airways, Nation Media Group, Standard Group, TPS East Africa Ltd, Uchumi Limited
Manufacturing	British American Tobacco Ltd, East African Breweries Ltd, Unga Group Ltd, Kenya Orchards Ltd, Athi River Mining Ltd, Bamburi Ltd, Crown Berger Ltd, East African Cables, East African Portland Cement Ltd
Energy and Transport	Car and General Kenya, Sameer Africa Ltd, Marshalls East Africa Ltd, KenolKobil Ltd, Total Kenya Ltd, Kenya Power and Lighting Company

3.3 Data analysis

3.3.1 Portfolio construction

The portfolios are constructed using the securities selected in the sampling process. The estimated portfolio return is a market capitalization weighted average of the stocks that belong to the specific industry category. Market capitalization weighting is preferred since it is simple to compute and serves as an indicator of the importance of the firm in the stock market. Therefore, the weight of stock i is:

$$W_i = \frac{Price_i * number\ of\ outstanding\ shares\ of\ stock\ i}{Total\ portfolio\ market\ capitalisation} \quad (3.1)$$

Where the market capitalization considered is as at June of year t.

3.3.2 General model specification and coefficient estimation

Considering a dynamic panel the model is specified as:

$$RM_t = \alpha_i + \lambda_i R_{i,_{t-n}} + \sum_{n=1}^{N} \beta_n RM_{t-n} + \gamma MVOL_{t-n} + \delta INF_{t-n} + \mu_{i,t} \quad (3.2)$$

Where $RM_t$is the excess return of the market in month t, $R_{i,t-n}$ is the lagged excess return of the industry portfolio i; RM_{t-n} is the lagged excess market return; $MVOL_{t-n}$is the lagged market volatility; INF_{t-n} is the lagged inflation; λ_i is the coefficient of interest which measures the ability of each of the industry portfolio to lead the market and $n = \{1,2, \dots N\}$ represents the number of lags.

The lagged market volatility acts as a control so as to ensure that the industry returns are predicting the actual market returns and not the market volatility. The monthly volatility is estimated from an ARCH (1) model of the stock index monthly returns.

Lagged excess market returns are also incorporated in the model so as to eliminate the possibility of autocorrelation given the possibility that today's returns are correlated to yesterday's returns. The lagged inflation incorporates an alternative explanation as to why the industries would be able to predict the market returns. Inflation is used as another control variable to represent the other macroeconomic variables that have been found to predict stock returns since inflation drives most of these macroeconomic variables such as interest rates. It is measured by the Central Bank of Kenya as:

$$Inflation_t = \frac{CPI\ INDEX_t - CPI\ INDEX_{t-1}}{CPI\ INDEX_{t-1}} * 100\%$$

Where t is the current month.

3.3.3 Information diffusion model

In order to capture the information diffusion effect, the following OLS regression is performed.

$$R_{i,t} = \alpha_{i,t} + \gamma_i MVOL_t + \delta_i INF_t + \varepsilon_t \tag{3.3}$$

Where $R_{i,t}$ is the excess return of industry portfolio i at time t.

The residuals from the OLS regressions above are then extracted and fitted in the information diffusion model below, which is informed by the news diffusion model specified by Rapach et al. (2013).

$$RM_t = \beta_1 \mu_{i,t-n} + \beta_2 \mu_{m,t} + \theta_i u_{i,t} + (1 - \theta_i) u_{i,t-n} \tag{3.4}$$

Where θ is the information diffusion coefficient, $\mu_{i,t-n}$ represents the lagged expected return of the industry portfolios and u represents the residuals extracted from the OLS regressions in equation 3.3.

3.3.4 Arellano-Bond GMM estimation

Equation 3.4 above is specified for each industry portfolio and a system of equations estimated using Arellano Bond GMM estimation as it accounts for possible endogeneity issues. See Hong et al. (2007) and Tse (2015) for details. The GMM estimation process is described below.

In equation 3.2 above: $\mu_{i,t} = \upsilon_i + \epsilon_{i.t}$ represents the fixed effects, that is: the industry specific effects υ_i and the observation specific errors $\epsilon_{i,t}$.Therefore, so as to remove the fixed effects and obtain a consistent GMM estimator, take the first differences such that:

$$\Delta RM_t = \lambda_i \Delta R_{i,_{t-n}} + \beta \Delta RM_{t-n} + \gamma \Delta MVOL_{t-n} + \delta \Delta INF_{t-n} + \Delta\epsilon_{i,t} \tag{3.5}$$

Simplifying equation 3.5 above:

$$RM_t = \beta \Delta RM_{t-n} + \theta \Delta x_{i,t-n} + \Delta\epsilon_{i,t} \tag{3.6}$$

Where x represents the vector of exogenous variables that are included in the model specification and $E[x_{i,t}, \upsilon_{i,s}] = 0\ for\ t\ and\ s = 1,2, \dots T\ and\ \rho(x_{i,t}, \mu_{i,t}) \neq 0$.

The resulting matrix of valid instruments (W_i) for the different time periods is:

$$\begin{bmatrix} [RM_1, x'_{i,1}, x'_{i,2}] & 0 & 0 \dots & 0 \\ 0 & [RM_1, RM_2, x'_{i,1}, x'_{i,2}] & 0 \cdots & 0 \\ \vdots & \vdots & \vdots \ddots & \vdots \\ 0 & 0 & 0 \cdots & [RM_1, RM_2, \dots RM_{T-2}, x'_{i,1}, x'_{i,2}, \dots x'_{i,T-1}] \end{bmatrix}$$

Where there are T rows in the matrix W and $W = [W_1', \dots W_N']'$

The matrix above indicates that as the number of time periods increase, the available dependent variable (RM_t) valid instruments also increase. This leads to improved efficiency of the estimator as there are more orthogonality conditions. The variables $x_{i,t}$ are also valid instruments given that $E[x_{i,t}, v_{i,s}] = 0\ for\ t\ and\ s = 1,2, \dots T\ and\ \rho(x_{i,t}, \mu_{i,t}) \neq 0$. They are therefore added to each diagonal term in the matrix as$\{x'_{i,1}, x'_{i,2}, x'_{1,3}, \dots x'_{i,T-1}\}$, where the number of valid instruments added depends on the time period.

The total number of moment equations (instruments) for the specified model are obtained using the formula:

$k + p * \frac{(p+1)}{2}$ where $p = T - 2, T$ is the total time period and k are the number of exogenous variables. (Baltagi, 2005)

Multiplying the differenced equation 3.6 by the vector form of W results in:

$$W'\Delta RM_t = W'\Delta RM_{t-n} + W'\theta(\Delta X) + W'(\Delta\epsilon) \tag{3.7}$$

Performing Generalized Least Squares (GLS) on equation 3.7 results in the preliminary AB one-step estimator. However, the one-step estimator is not efficient. Therefore, to obtain the two-step efficient estimator, the first step residuals are used to estimate the variance-covariance matrix of the moment conditions.

Thus, the one-step and two-step estimators can be estimated using the equation:

$$\binom{\hat{\delta}}{\hat{\theta}} = ((\Delta RM_{t-n}, \Delta X)' W \hat{V}_N^{-1} W' [\Delta RM_{t-n}, \Delta X])^{-1} \left([\Delta RM_{t-n}, \Delta X]' W \hat{V}_N^{-1} W' \Delta RM\right) \qquad (3.8)$$

Where W' represents the weighting matrix

Lastly, two specification tests are performed once the GMM estimators are obtained. The first is the Arellano-Bond test for autocorrelation of the error terms of the first difference equation, as defined by Arellano & Bond (1991). The second specification test is the Sargan test for over-identifying restrictions which is expressed as:

$$m = \Delta\widehat{v'} W \left[\sum_{i=1}^{N} W'_i (\Delta\hat{v}_i)(\Delta\hat{v}_i)' \, W_i\right]^{-1} W'(\Delta\hat{v}) \sim \chi^2_{p-K-1}$$

Where p refers to the number of columns in the weighting matrix W and $(\Delta\hat{v})$ are the residuals from the two-step GMM estimation. (Baltagi, 2005)

3.3.5 Pairwise Granger Causality tests

The Granger Causality Test is used to determine the direction of the causal relationship between the industries and the stock market.

The equations estimated that will facilitate the hypotheses tests are:

$$RM_t = \alpha_i + \sum_{i=1}^{m} \lambda_i R_{i,_{t-n}} + \sum_{i=1}^{m} \beta RM_{t-n} + \gamma MVOL_{t-n} + \delta INF_{t-n} + e_{i,t} \qquad (3.9)$$

$$R_{i,t} = \alpha_i + \sum_{i=1}^{m} \lambda_i R_{i,_{t-n}} + \sum_{i=1}^{m} \beta RM_{t-n} + \gamma MVOL_{t-n} + \delta INF_{t-n} + e_{i,t} \qquad (3.10)$$

The hypothesis to test if the industry portfolios Granger-cause the market returns are:

$H_{1,0}: \lambda_1 = \lambda_2 = \cdots \lambda_n = 0$

$H_{1,a}: \lambda_1 \neq \lambda_2 \neq \cdots \lambda_n \neq 0$

While those to test the inverse directional relationship are:

$H_{2,0}: \beta_1 = \beta_2 = \cdots \beta_n = 0$

$H_{2,a}: \beta_1 \neq \beta_2 \neq \cdots \beta_n \neq 0$

3.4 Robustness check

In order to assert the validity of the model, an alternative weighting scheme such as equal weighting is used in the construction of the industry portfolios. This accounts for the fact that market capitalization weighting could lead to bias towards the larger securities in the portfolio. Also, changing the broad market proxy to the NSE All-share Index checks the consistency of the market indicators.

4 FINDINGS AND ANALYSIS

4.1 Pre-estimation tests

4.1.1 Contemporaneous correlation between returns and excess returns

Table 2: Correlation matrix for returns and excess returns

	Agric.	FS	C&S	M&A	E&T
Agric.	1				
FS	0.652392	1			
C&S	0.107633	0.214634	1		
M&A	0.789679	0.816825	0.176752	1	
E&T	0.695003	0.807903	0.258035	0.779084	1
Agriculture	0.965721	0.644349	0.10162	0.762692	0.680744
Financial Services	0.420057	0.473503	0.074997	0.413496	0.416632
Commercial & Services	0.287592	0.283877	0.339513	0.256791	0.291971
Manufacturing	0.523195	0.498873	0.08311	0.553497	0.479564
Energy and Transport	0.456443	0.456484	0.099358	0.433385	0.511669

In the table above, monthly returns are represented in the abbreviated form of the portfolio names while excess returns are those represented in the full portfolio name.

The results reveal that there is a positive correlation between returns and excess market returns. The highest observed correlation is between the returns and excess returns of the agriculture industry portfolio with a correlation coefficient of 0.9657 while the lowest is that of the commercial and services portfolio with a correlation coefficient of 0.3395.

These results inform the decision to use excess returns in the model estimation.

4.1.2 Contemporaneous correlation between the market and the industry returns

Table 3: Correlation matrix for excess market returns and excess industry returns

	Agriculture	Financial Services	Commercial and Services	Manufacturing	Energy and Transport	Excess Market returns
Agriculture	1					
Financial Services	0.63546	1				
Commercial and Services	0.51220	0.932491	1			
Manufacturing	0.71839	0.97695	0.90302	1		
Energy and Transport	0.66414	0.98248	0.92698	0.97230	1	
Excess Market returns	0.291	0.53787	0.53727	0.53895	0.52379	1

From the results, there is a positive correlation between the excess market returns and the excess industry portfolio returns. The highest correlation is between the market and the manufacturing industry with a coefficient of 0.5389 while the lowest is between the market and the agriculture industry with a coefficient of 0.291.

The positive correlation is indicates that the industries and the overall market move in the same direction. However, the strength of the relationship varies with all industries having a strong relationship (coefficients greater than 0.5) except the agriculture industry which has a weak relationship (coefficient of 0.291 which is less than 0.5)

4.1.3 Correlation between excess market return and lagged industry excess returns

Table 4: Correlation matrix for excess market returns and industry returns lagged once

	Agriculture (-1)	Financial Services (-1)	Commercial and Services (-1)	Manufacturing (-1)	Energy and Transport (-1)	Excess Market returns
Agriculture(-1)	1					
Financial Services (-1)	0.62397	1				
Commercial and Services(-1)	0.5173	0.9377	1			
Manufacturing (-1)	0.7237	0.9798	0.9031	1		
Energy and Transport (-1)	0.6588	0.9826	0.9295	0.9732	1	
Excess Market returns	0.2303	0.4145	0.3992	0.4145	0.3990	1

Table 5: Correlation matrix for excess market returns and excess industry returns lagged twice

	Agriculture (-2)	Financial Services (-2)	Commercial and Services (-2)	Manufacturing (-2)	Energy and Transport (-2)	Excess Market returns
Agriculture (-2)	1					
Financial Services (-2)	0.6032	1				
Commercial and Services (-2)	0.5164	0.9431	1			
Manufacturing (-2)	0.7001	0.9807	0.9159	1		
Energy and Transport (-2)	0.6393	0.9819	0.9353	0.9733	1	
Excess Market returns	0.2257	0.2798	0.3039	0.3312	0.3035	1

Correlation between the excess market returns and the industry excess returns remains positive after lagging the industry returns both once and twice. However, the incorporation of more lags weakens the relationship further. For example, the correlation between the market and the agriculture industry declines from 0.291 to 0.2257.

4.1.4 Time series properties of the excess return series

The results of the Augmented Dickey Fuller test are listed in the table below.

Table 6: Results of the Augmented Dickey Fuller test

Industry	**Stationarity (Augmented Dickey Fuller Test)**
Market	Stationary at all levels
Agriculture	Non-stationary
Commercial & Services	Stationary
Financial Services	Non-stationary
Manufacturing	Stationary only at 5% and 10% level
Energy and Transport	Stationary at 10% level

The results indicate that the financial services and agriculture portfolio excess returns are non-stationary. The first differencing technique is used to transform the data so that it is stationary. The first differences of all the industry excess returns and the market excess returns are taken so as to ensure that all the variables are integrated to the same level when performing the OLS regressions.

4.2 GMM estimation results

In the GMM estimation of the system of equations specified as per equation 3.4, market volatility and inflation are used as instruments. The Two-Stage Least Squares (2SLS) and GMM robust standard errors is used as the identity weighting matrix in the estimation.

The information diffusion coefficients (θ) obtained from the system of equations estimated for each industry are all insignificant. The insignificant coefficients are observed regardless of the changes made in the specification of equation 3.4. For example, where β_1 varies across industries, the results obtained are:

Table 7: Information diffusion coefficients estimated using Arellano Bond GMM estimation

	Agriculture	Commercial & Services	Financial Services	Manufacturing	Energy & Transport
β_1	1.204913	20.40590	7.089755	15.48961	10.87234
p-value	0.9998	0.9998	0.9998	0.9998	0.9998
θ_i	2.180739	6.879410	3.974496	3.592643	6.956107
p-value	0.9994	0.9997	0.9996	0.9996	0.9997

β_2 is estimated as 26.17382 with a p-value of 0.9998. The Hansen J-statistic is 0.031892 with a chi-square p-value of 0.9985. This indicates that the J-statistic is insignificant thus we reject the null hypothesis that the instruments are invalid and the structural equation is incorrectly specified.

Overall, the results indicate that there is neither information diffusion nor excess stock return predictability. These findings contradict those of Rapach et al. (2013) who find significant gradual information diffusion coefficients for the US market to the other non-US markets. This gives rise to the ability of the lagged US market returns to predict the non-US market returns.

The absence of stock market return predictability for any portfolio at any lag level is also inconsistent with the results of Hong et al. (2007) who find that with a 1 month lag, 14 out of 34 industries are able to predict the stock market; and Tse (2015) who finds that with 3 lags, 4 out of 48 industries are able to predict the stock market at the 10% level of significance.

However, the absence of return predictability is consistent with the results obtained by Tse (2015) who finds that after changing the model specification to include higher lag lengths on the dependent variable among other changes, there is neither gradual information diffusion nor stock return predictability.

Therefore, while the results of this study are inconsistent with those that find there is stock return predictability as a consequence of gradual information diffusion, they are consistent with those of the EMH.

4.3 Pairwise Granger Causality results

The pairwise Granger Causality test results between the market and the industries are listed in the table below.

Table 8: Pairwise Granger Causality test results

Null Hypothesis	F-statistic	Probability	Decision
Excess Market return does not Granger Cause Agriculture	0.97299	0.3808	Accept
Agriculture does not Granger Cause Excess Market Return	1.14302	0.3222	Accept
Excess Market return does not Granger Cause Financial Services	1.70963	0.1852	Accept
Financial Services does not Granger Cause Excess Market Return	0.43613	0.6475	Accept
Excess Market return does not Granger Cause Comm. & Services	0.27608	0.7592	Accept
Comm. & Services does not Granger Cause Excess Market Return	1.25132	0.2897	Accept
Excess Market return does not Granger Cause Manufacturing	1.16269	0.3161	Accept
Manufacturing does not Granger Cause Excess Market Return	0.94016	0.3934	Accept
Excess Market return does not Granger Cause Energy & Transport	0.38108	0.6839	Accept
Energy & Transport does not Granger Cause Excess Market Returns	0.72906	0.4844	Accept

The results indicate that there is no causal relationship between the market and the industries in either direction.

Industry pairwise causality test results indicate that both financial services and manufacturing granger cause energy and transport and commercial and services. Energy and transport also

Granger causes commercial and services. Lastly, financial services Granger causes manufacturing but manufacturing also Granger causes financial services.

The Granger causality test results between the market and the industries are inconsistent with those of Hong et al. (2007) who finds that there is a causal relationship between the market and the industry portfolios and the direction of this relationship is from the industries to the market. Furthermore, they are also inconsistent with the results of Tse (2015) who despite disagreeing with Hong et al. (2007) on the direction of the causal relationship concludes that there exists a causal relationship between the market and industry portfolios.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

Previous research on stock market return predictability in the Kenyan market has only attributed the presence of stock market return predictability to market inefficiency and as such has failed to consider alternative explanations to the EMH such as gradual information diffusion. This study investigates if excess industry portfolio returns are able to predict excess stock market returns in the presence of information diffusion for the Kenyan market between 2005 and 2015.

A system of equations is specified and GMM estimation is used to estimate the information diffusion coefficients for each industry as well us to test the existence of stock market return predictability. The pre-estimation test results indicate that there is a positive relation between the excess NSE 20 stock market returns (which serves as a proxy for the overall market) and the industry portfolio returns. While the relationship is positive between all industries and the market, the strength of the relationship varies. For example, the agriculture industry is found to have a weaker relationship with the market than the financial services industry as evidenced by the correlation coefficients of 0.291 and 0.5389 respectively.

From the GMM estimation, the information diffusion coefficients obtained are found to be insignificant for all industry portfolios. Furthermore, the pairwise Granger causality test results indicate that neither the industries Granger cause the stock market nor does the market Granger cause the industry portfolio returns.

Therefore, the results of this study suggest that in the case of the Kenyan Stock market, while the overall market and the industries are observed to move in the same direction, there does not exist a causal relationship between the market and the industries in either direction. Additionally, there is no information diffusion or stock return predictability in the Kenyan market, which is consistent with the EMH.

5.2 Limitations of the study and recommendations for future study

One significant limitation of the study is the insignificant information diffusion coefficients. These results can be improved upon by exploring a non-linear relationship between the variables as opposed to the linear relationship in the information diffusion model used in this study. Alternatively, a different information diffusion model that would be able to capture more accurately the dynamics of the Kenyan stock market should be developed.

Future research could also focus on identifying variables in addition to or that would perform better than market volatility and inflation as control variables.

Lastly, this study can be extended by enlarging the sample to include other African countries.

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