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Stock Markets' Dynamics in Oil-Dependent Economies: Evidence from the GCC Countries

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Abstract

This paper investigates the relationship between stock prices and main macroeconomic variables (i.e. oil prices, short-term interest rates and domestic credit) that are believed to affect stock prices in the context of the Gulf Cooperation Council (GCC) markets. For this purpose, this paper employed recent time series techniques of cointegration and Granger Causality Analysis. The multivariate cointegration tests identified that oil prices, interest rates and domestic credit have long-term equilibrium effects on stock market prices in four GCC countries. In addition, the Granger Causality Analysis highlighted that the causality is running from oil prices to the stock price index in the case of Kuwait, Saudi Arabia and Oman. Also, the causal flow from domestic credit to the index has been found in the case of Kuwait and Saudi Arabia; while the interest rate has a causal effect on the stock price index in the case of Saudi Arabia, Bahrain and Oman. Further assessment of the relationship between these variables, based on generalized variance decomposition and generalized impulse response functions, reveals the importance of oil prices in explaining a significant part of the forecast error variance of the index in Kuwait, Saudi Arabia and Oman. Most of the variations in the stock prices can be captured by innovations in the three selected variables. Therefore, the causal relationship that the macroeconomic variables Granger - caused stock prices is quantitatively supported by innovation analysis.

Key words: Stock Markets' Dynamics, Macroeconomic Factors, GCC
I. INTRODUCTION

During the last few years, the stock markets in the GCC countries have grown enormously in terms of market capitalization and trading turnover. For example, the GCC stock markets’ capitalization increased from $112bn at the end of 2000 to approximately $1,061bn at the end of 2005. This represents a growth of 850% in a period of less than five years.\(^1\) In terms of domestic market capitalization, the combined stock markets of the GCC countries are now larger than the Hong Kong Stock Exchange and nearly one-third the size of the London Stock Exchange.

The GCC market indices illustrate the extraordinary level of investor interest in the GCC stock markets. During 2005, the General Price Index in Saudi Arabia increased by 82%, the index of the Doha Securities Market increased by 91%, and that of the Dubai Financial Market increased by 171%. The Saudi stock market accounted for more than half of the GCC markets’ capitalization at the end of 2005 at $660bn, 116% increase from its end-2004 value of $306bn. The combined capitalization of the Abu Dhabi and Dubai markets grew to $234.4bn at the end of 2005, up by 63% from $144bn in 2004. Qatar’s market value grew from $40.4bn at the end of 2004 to $87.1bn in 2005, a gain of 115.6%. The Kuwaiti Stock Exchange capitalization rose 90% to $140bn in 2005, from $73.8bn in 2004; while the relatively smaller stock markets in Bahrain and Oman increased by about 29% and 24% in 2005 respectively. The trading turnover in the seven stock exchanges (discussed above) also surged by 148% to $1.368 trillion from $552bn in 2004. The Saudi market accounted for $1.1 trillion or 80% of turnover in all the GCC stock markets. It was followed by UAE markets with $138.9bn and Kuwait with $97.3bn. The Dubai Index rose 132.4%, followed by the Saudi Index, which gained 103.7%. The Kuwaiti index rose

\(^{1}\)See www.ameinfo.com/financialmarkets.
by 78.6%, Qatar by 70.2%, while Abu Dhabi increased by 69.4%. The markets of Oman and Bahrain rose by 44.6% and 23.8%, respectively. Furthermore, real gross domestic product growth for the region grew at an average of around 8.5% in 2003, 5.9% in 2004, 6.8% in 2005, and 6% in 2006.

Three factors appear to have had an impact on the strong and unique performance of the GCC stock markets over the last few years: high oil prices, abundant levels of liquidity in the region, and the decline in interest rates. Oil prices rose from $25 in 2002 to $60 in 2006 to $90 in 2007. Since the GCC countries are major suppliers of oil in the world energy market and they collectively possess 47% of the world’s proven oil reserves and account for 24% of global petroleum production and 40% of petroleum exports, oil revenues largely determine their government budget revenues and expenditure. Thus, oil revenues are crucial components of aggregate demand in these countries. The aggregate demand highly influences corporate activities and domestic price levels, which in turn affect corporate earnings and stock prices.

Despite many efforts to diversify their economies, GCC countries remain over dependent on oil, and around 80% of their budget revenues are due to oil. In this economic environment, the combination of limited business diversity and excess liquidity favored the surge of their stock markets, and made it normal for these markets to witness much activity. For example, the domestic liquidity over 2001-2005 increased by 50%, 65%, 50%, and 36% in Kuwait, Saudi Arabia, Bahrain, and Oman respectively. This increase has directly or indirectly fed a rapid rise

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2 See each exchange's website:

in demand for credit from the real economy, improving access for finance for corporations, facilitating the strong growth in investment and hence surging stock markets.

The other important factor that may impact the stock market activity in the GCC countries is the low interest rates, which are mainly driven by the sensitivity of the GCC interest rates to changes in the US Treasury bill rate as a result of fixing their national currencies to the US dollar. Most of the GCC countries fixed their currencies to the US dollar many years ago, whether one to one or through a basket of currencies dominated by the dollar. Thus, GCC countries by nature are overly sensitive to global factors, such as oil prices and US Treasury bill rates and domestic factors such as excess liquidity.

Nevertheless, a considerable body of literature establishes credible evidence that stock markets are affected by a number of key macroeconomic variables. However, it is quite clear that most of empirical studies related to this issue remained confined to world major stock markets with highly diversified productive sectors. Such studies include Fama (1981, 1990); Chen, Roll and Ross (1986); Hamao (1988); Eun and Shim (1989); Asperm (1989); Kim and Wadhwani (1990); Joen and Von Furstenberg (1990); Thornton (1993); Arshanapalli and Doukas (1993); Kasa (1992); Kaneko and Lee (1995); Cheung and Ng (1998); Darrat and Dickens (1999). For example, Fama (1981) asserts that there is a strong relationship between stock prices and macroeconomic variables such as GNP, money supply, capital expenditure, industrial production and interest rate. Similarly, Chen, Roll and Ross (1986) find a relationship between stock market prices and macroeconomic factors such as inflation, industrial production, money supply, exchange rate, and interest rate.

Few studies that have been conducted on developing countries include Mookerjee and Yu (1997), Maysami and Koh (2000) for Singapore; Kwon, Shin, and Bacon (1997) and Kwon and Shin
(1999) for South Korea; Habibullah and Baharumshah (1996) and Ibrahim (1999) for Malaysia. For example, Mookerjee and Yu (1997) note a significant relation between money supply and foreign exchange reserves and stock prices for the case of Singapore. However, Maysami and Koh (2000) find a significant relation between Singapore’s stock prices and various macroeconomic variables, such as interest rate and exchange rate. Kwon, Shin, and Bacon (1997) study the Korean equity market and find evidence for the exchange rate, dividend yield, oil price and money supply as being significant macroeconomic variables. Similarly, Kwon and Shin (1999) establish a long-run relation between stock prices and industrial production, exchange rate, trade balance and money supply for Korea.

While most studies have been conducted on developed countries and a few on developing countries, similar work about the fast-growing emerging markets (i.e. GCC stock markets) is almost non-existent. Despite their importance, only handful of studies have been conducted on these markets, such as Assaf (2003), Hammoudeh and Aleisa (2004), and Hammoudeh and Choi (2006). Assaf (2003) investigates the dynamic relationship among the GCC markets during the period 1997-2000 using Vector Error Correction models. He finds strong interaction and feedback among these markets. Specifically, Assaf indicates that Bahrain’s market has a dominant role in influencing the other GCC markets, while Saudi Arabia’s market is slow in receiving shocks from these markets. Hammoudeh and Aleisa (2004) examine the link between the indices of five GCC stock markets and between the indices and the future prices of oil. They use daily data for the period 1994-2001. Their findings suggest that the Saudi index has the most causal linkages with the other GCC markets, and it can explain and predict all the GCC indices at five percent level of significance. The Bahrain index is the second most linked with the other GCC markets. On the other hand, the Kuwaiti market has the least causal linkages, followed by
the Omani market. Furthermore, they find that there is bidirectional relationship between the Saudi index and the future oil prices. The oil prices also can predict and explain the other GCC indices, with the exception of the United Arab Emirates’ index.

Hammoudeh and Choi (2006) investigate the relationships among five GCC stock markets and their link to three global factors: oil spot prices, the US Treasury bill rate and the Standard and Poors index over the period 1994-2004. They find that despite the long-run relationships, these markets do not have a strong predictability power for each other. Also their results suggest that the US Treasury bill rate has a short-term impact on some of the GCC stock markets. However, the oil prices and S&P index have no predictability effect on any market in the short term.

These studies mainly focus on the dynamic relationships among the GCC stock market returns rather than the impact of economic activity on the stock market movements. So far, to our knowledge, no work has been done on the impact of both local and global macroeconomic factors on stock markets in the GCC countries. Furthermore, the data used in the above mentioned studies predate the end of 2001, thereby missing the rapid and important changes that have taken place in the GCC markets in the last few years. They also neglect to incorporate the influence of local factors such as money supply as a measure of the liquidity in the economy. For example, Beckers, Connor and Curds (1995) find both global and national factors are of equal importance in explaining the co-movement of stock returns, while national factors are dominant in explaining the stock return volatility.

Thus, this paper contributes to the existing literature mainly by including a local variable (domestic credit), in addition to two global economic factors (oil prices and US Treasury rate).

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4 Hammoudeh and Choi (2006) focus only on the global factors.
6 Similar results were found by Grinold, Rudd, and Stefek (1989), Drummen and Zimmermann (1992), and Heston and Rouwenhorst (1994).
Also, this is the first study uses a combination of methodology consists of both innovation analysis and Granger Causality Analysis together. Furthermore, GCC stock markets belong to economies whose general features are not consistent with the standard profile encountered in recent relevant literature. The unique features of these economies render the determination of stock prices in these markets significantly different from those in other countries. Not all variables used in previous studies would be suitable in the case of the GCC markets. For example, many of the standard macroeconomic variables such as industrial production index and inflation rate, which are commonly used as proxies of economic activities, would have little relevance as determinants of stock prices in the context of GCC countries. For example, GCC countries enjoy a low level of inflation which undermines the effect of such variables on GCC stock markets. From this perspective, this paper proposes to analyze the stock markets using the variables that reflect those unique features of GCC economies and are believed to impinge on the working of these markets, notably oil prices, US Treasury bill rate, and money supply.

In addition, we know there is a direct link between the underlying economy and asset prices for most developed and some developing countries. However, we do not know enough about the relationship between the underlying economy and asset prices for economies that rely on the export of a single product: namely, oil. Given that oil prices are determined by demand and supply at the world level, it would be interesting to know whether asset prices in oil exporting countries simply reflect changes in the value of the dollar and the developments in the world economy or whether they respond to domestic macroeconomic shocks as well. Although all GCC

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7 Most of the studies on the link between economic activities and stock prices used the industrial production index as a proxy of macroeconomic activities (e.g. Fama (1981, 1990), Schwert (1990), Lee (1992) for the United States; Wasserfallen (1989) for Germany, Switzerland and the UK; Asprem (1989) for a group of European countries; Peiro (1996) for Germany, France, the UK and the US; Binswanger (2001) for G-7 countries).

8 Only in the last two years has the inflation rate increased to about 8% to 10% in both the UAE and Qatar while it remains low in the other GCC countries. Both the UAE and Qatar are not included in our analysis due to lack of consistent monthly data for these countries.
countries performed very well over the last few years, their individual performances were not alike and their link to oil is not the same; therefore, they are worthy of further investigation. Finally, the investigation of the dynamic relationship between stock prices and macroeconomic variables becomes more and more important for smaller stock markets as their economic role is less understood compared to well-organized and mature markets as they are less liquid and said to be more affected by speculations and government interventions.

Motivated by the lack of literature on the link between the macro-economy and stock prices in oil exporting countries such as the GCC countries, our investigation attempts to widen the scope of this line of research by extending this type of analysis to select GCC economies with different profiles than those already investigated in the literature. Undoubtedly, valuable insights could be gained from such investigations, thus allowing for meaningful comparisons of the impact of various economic forces on stock markets across economies with different characteristics. Given that these economies are well-integrated in the world economy; this study can be considered an important contribution to the investigation of small open economies. Such investigation would be very helpful to policy makers and the investing community.

The rest of the paper is organized as follows. Section 2 presents the econometric methodology employed in this paper. Section 3 discusses the variable definitions and data sources. Section 4 reports the empirical results and section 5 concludes.

II. ECONOMETRIC METHODOLOGY

This paper employs the multivariate cointegration analysis, the Granger Causality Analysis in the context of vector error correction model (VECM), the generalized variance decompositions and the generalized impulse response functions to analyze the dynamics of stock prices in GCC stock markets. As is common in the literature related to time series techniques, the first step in
determining whether common stochastic trends are present among the variables is the detection of a unit root test in each series. For this purpose, this paper employs the well-known Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. These tests are performed on both the level variables and their first differences, with the null hypothesis being that the variable under investigation has a unit root against the alternative that it does not. A time series is stationary when its mean and variance are constant over time (i.e. it has no trend and the value of the covariance between two periods depends only on the distance or lag between the two periods and not on the actual time at which the covariance is computed). The use of no stationary variables in a given model leads to the spurious regression phenomenon discussed by Granger and Newbols (1986) and Phillips (1987). Moreover, Stock and Watson (1998) have also shown that the usual test statistics (t and F) will not possess standard distributions if some of the variables in the model have unit roots and are thus, not stationary.

II.i Multivariate Cointegration Tests and VEC model

Having established that the variables are integrated in the first difference, and since we are interested in modeling a long-run relationship between macroeconomic variables and stock prices, cointegration analysis is an ideal tool. We proceed to the estimation of the number of cointegration vectors using Johansen (1988) and Johansen and Juselius (JJ) (1990) approach. Several advantages of this approach have been identified over its predecessor, popular residual-based Engle-Granger two-steps approach in testing for cointegration. Firstly, the JJ procedure does not assume the existence at most of a single cointegrating vector; rather it explicitly tests for the number of cointegrating relationships. Secondly, different from Engle-Granger procedure which is sensitive to the choice of the dependent variable in the cointegration regression, the JJ procedure assumes all variables to be endogenous; and when it comes to extracting the residual
from the cointegrating vector, the JJ procedure avoids the arbitrary choice of the dependent variable as in the Engle-Granger approach, and is insensitive to the variable being normalized. Thirdly, the JJ procedure is established on a unified framework for estimating and testing cointegrating relations within the VECM formulation. Fourthly, JJ provides the appropriate statistics and the point distributions to test the hypothesis for the number of cointegrating vectors and tests of restrictions upon the coefficients of the vectors. For these reasons, we follow the multivariate test for cointegration advocated by Johansen (1988) and Johansen and Juselius (JJ) (1990).

Consider the following vector autoregressive (VAR):

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_k Y_{t-k} + \mu + \eta_t$$

where $Y_t$ is a $k*1$ vector containing the variables of our analysis. Suppose that these variables are I(0) after applying the difference filter once. If we exploit the idea that the relevant variables move together over time toward a long-run equilibrium state, then by the Granger Causality Analysis we may posit the following testing relationship that constitutes a VECM model:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \ldots + \Gamma_k \Delta Y_{t-k+1} + \Pi Y_{t-k} + \mu + \eta_t$$

where $\Delta Y_t$ is the vector of first differences of the variables, the $\Gamma$'s are the estimated parameters, $\Delta$ stands for the operator difference, $\eta_t$ is a vector of impulses which represents the anticipated movements in $Y_t$, with $\eta_t \approx niid(0, \sum \sigma^2)$ and $\Pi$ is the long-run parameters matrix. With $r$ cointegrating vectors ($1 \leq r \leq k$), $\Pi$ has rank $r$ and can be decomposed as $\Pi = \alpha \beta$, with $\alpha$ and $\beta$ both $k*r$ matrices. $\beta$ are the parameters in the cointegrating relationship and $\alpha$ is the adjustment coefficients which measure the strength of cointegrating vectors in VECM.
The Johansen (1988) and Johansen and Juselius (JJ) (1990) multivariate cointegration techniques allow us to estimate the long-run relationship between variables, using two likelihood ratio test statistics: the trace statistic and the maximum Eigen value statistic. They can be used for testing cointegrating vectors. The hypothesis that there are at most r distinct cointegrating vectors can be tested by the trace statistic: Trace test: \(-T \sum_{i=r+1}^{n} \ln (1- \lambda_i)\); where T is the number of observations and \(\lambda_s\) are Eigen values between the two residuals \(R_0\) and \(R_1\). Alternatively, the maximum Eigen values statistic tests the hypothesis of \(r+1\) cointegrating vectors, given \(r\) cointegrating vectors and is defined as: Maximum \(\lambda\) test: \(-T \ln (1- \lambda_{r+1})\); where \(\lambda_{r+1}\) is the \((r+1)\) largest Eigen value. The trace tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to \(r\) against the general alternative. The maximum Eigen value tests the null hypothesis of \(r\) cointegrating vectors against \(r+1\) cointegrating vectors. The critical values for both tests are available in Oster-Lenum (1992). Johansen (1991, 1992) proved that the intercept terms in the VEC model should be associated with the existence of a deterministic linear trend in the data. However, if the data do not contain a time trend, the VEC model should include a restricted intercept term associated to the cointegrating vectors.

The vector error correction model shows how the system is adjusting in each time period toward its long-run equilibrium state. Since the factors are supposed to be cointegrated, then in the short run, any deviations from the long-run equilibrium will feed back on the changes in the dependent variables in order to force their movements toward the long-run equilibrium state. Consequently, the cointegrating vectors from which the error correction terms are derived are each indicating an independent direction where a stable long-run equilibrium state exists. However, the coefficients
of the error correction terms represent the proportion by which the long-run disequilibrium in the dependent variables is corrected in each term period.

II.ii Causality Tests

After conducting the cointegration tests, we proceed by applying Granger Causality Analysis, which enables us to investigate the direction of the relationship between the stock index and the macroeconomic variables. More specifically, we can examine whether the macroeconomic variables have an effect on the stock index or they are affected by it. Cointegration analysis allows proving the existence of the relationship but does not allow us to conclude about the direction of the causality. Granger (1986) indicates that if two variables are cointegrated, then Granger Causality must exist in at least one direction. This result is a consequence of the relationship described by the VECM. Since the variables move together over time, then any variable or a combination of any of the variables in $\Delta Y_t$ must be Granger-caused by the lagged values of the level variables. Given this, the causal relation between the variables can be investigated using the joint F-test applied to the coefficient of each explanatory variable and the coefficient of the cointegrating vector in the VECM.

II.iii Variance Decompositions and Impulse Responses

In order to analyze the dynamic properties of the variables under analysis, we employ the generalized variance decomposition and the generalized impulse response functions. The purpose of this investigation is to find how the index responds to shocks by other variables of the system. The forecast error of generalized variance decompositions analysis reveals information about the proportion of the movements in sequence due to its “own” shocks versus shocks to other variables. If the shocks do not explain any of the forecast error variance of one macroeconomic variable in all forecast horizons, then this variable is exogenous. On the opposite side, if shocks
can explain all forecast error variance of the variable at all forecast horizons, this variable is an entirely endogenous variable. The generalized impulse response functions provide an estimate of the response of a variable in the case of innovation in another variable. Plotting the generalized impulse response functions is a practical way to explore the response of a variable to a shock immediately or with various lags.

In calculating variance decompositions and impulse response functions, it is assumed that the variables should be in a particular order. However, according to Koop, Pesaran, and Potter (1996), unlike orthogonalized variance decomposition and impulse response functions obtained using the Cholesky factorization, the generalized variance decomposition and impulse response functions are unique and invariant to the ordering of the variables in VAR.

III. DATA

In choosing the relevant variables to include in the model we rely on earlier empirical analysis and economic intuition. As discussed earlier, many of the well-known macroeconomic variables that are well-defined in the literature to be related to the stock markets have probably little bearing on the stock market in GCC countries. Based on this point of view, we hypothesize a relationship between GCC stock prices and several variables that we view to be most pertinent to the GCC stock markets’ setting. In line with the following empirical studies - Chen, Roll and Ross (1986), Mookerjee and Yu (1997), Maysami and Koh (2000), Kwon, Shin, and Bacon (1997), Kwon and Shin (1999), Habibullah and Baharumshah (1996), Ibrahim (1999), Assaf (2003), Hammoudeh and Aleisa (2004) and Hammoudeh and Choi (2006) – the three macroeconomic factors that are used in the present study: oil prices, interest rates, and money supply.
The first variable, which is believed to impinge on the working of the stock markets in the GCC, is the price of oil. This choice is built on the fact that GCC economies depend mainly on oil revenues. Oil revenues are considered the main source of income and government spending. As known, the profitability of the business sector is largely affected by the level of economic activity. Since the oil prices (oil revenues) are the major component of the gross domestic product in the GCC countries, an increase in oil prices, by affecting economic activity and corporate earnings, has implications for asset prices and stock markets. However, given the recent fast developments in the GCC stock markets, it is unclear to what extent the recent increase in the oil price has been directly responsible for recent turbulence in their stock markets. This strong influence of oil prices on the national economies of GCC countries makes it interesting to investigate the impact of oil prices on their stock markets’ movements. Furthermore, understanding the link between oil prices and stock prices is important for investors in order to make the right investment decisions and for policy makers in order to adopt the appropriate policies to develop the stock markets.

The financial economics literature suggests that monetary policy instruments are considered one of the most important mechanisms that affect stock markets. For example, changes in interest rate or domestic liquidity in the economy force the participants in the stock markets, and investors in general, to reconsider their investment strategies because, as suggested by financial theories, the value of an asset today is the sum of the discounted future cash flows from this asset. As we discussed earlier, most of the GCC countries tie their exchange rates effectively to the US dollar. Consequently, GCC monetary policies should follow US monetary policy, resulting in a highly correlated relationship between their short-term interest rates and US rates as suggested by the

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9 The correlation coefficients between oil prices and GDP are .95, .93, .92, and .92 for Kuwait, Saudi Arabia, Bahrain, and Oman, respectively. It is noteworthy that GDP is not available on a monthly basis; oil price is the best proxy for it.
The hypothesis of interest rate parity. The correlation coefficients between local short-term interest rates in the GCC and US Treasury bill rate are about 94%, 97%, 99%, and 70% for Kuwait, Saudi Arabia, Bahrain, and Oman respectively. This fixing of exchange rates makes the movements of the local interest rates very close to the US rates, which have been low over the past years, contributing to lower rates in the GCC countries. Based on this argument, the short-term interest rate for the four countries is proxied by the US Treasury bill rate.

Theoretically, an increase in interest rates raises the required rate of return, which in turn inversely affects the value of the asset. Considered as opportunity cost, the nominal interest rate will affect investors’ decisions on asset holdings. An increase in this opportunity cost will motivate them to substitute their equity shares for other assets in their portfolio. Thus, an increase in interest rates has a negative effect on stock prices from the perspective of asset portfolio allocation. Furthermore, an increase in interest rates may restrain economic activity and cause a decline in future corporate profitability. Therefore, a negative relation between interest rates and stock prices is expected.

In addition to the oil prices and US Treasury bill rate, we choose another variable which reflects the liquidity in the economy. This variable is the money supply proxied by domestic credit. As known, all GCC countries fix their currency exchange rate to the US dollar. Under these circumstances, where there is no independent monetary policy, money supply will have a limited role as an indicator of liquidity in the economy; so, given the structure of the GCC countries, domestic credit appears to be an appropriate measure of liquidity and a good proxy for money supply (henceforth, we use domestic credit to describe money supply). The rationale of including such variables is that we have to have a factor reflecting the liquidity effect on the stock prices.

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10 Appendix is available upon request.
11 The results (not reported) of correlation coefficients between money supply and domestic credit are .90, .70, .98 and .90 for Kuwait, Saudi Arabia, Bahrain and Oman, respectively.
An increase in liquidity creates an excess supply of money balances and an excess demand for equity, and results in an increase in equity prices. However, in the long run an increase in liquidity will cause inflation and increase interest rates, which in turn will increase the discount rate in the valuation model. Therefore, the stock prices may be negatively related to domestic credit. Note, however, in the case of the GCC countries, the inflation rate was low in the period under investigation. Thus, we hypothesize that the domestic credit may have a positive effect on stock prices.

Monthly data in logarithmic form used for the period 1994:10 to 2007:12 for Kuwait, Bahrain, and Oman and for the period 1996:1 to 2007:12 for Saudi Arabia are used in this investigation. The starting date was dictated by data availability and the need to maintain consistency. Monthly data frequency is chosen in order to avoid potential spurious correlations among the time series often found to exist in aggregated quarterly and annual data. On the other side, data frequency shorter than a month is constrained by the fact that one of our variables (domestic credit) is available only on a monthly basis. It is assumed that stock prices are related to some macroeconomic variables, and hence time series, which may be able to capture both current and future directions in the broad economy. Hence the variables are: value weighted stock price index (INDEX), crude oil price (OIL), short-term interest rate (INT) and domestic credit (DC). The index variable has been obtained from the Arab monetary funds (AMF); the oil price obtained from US energy information administration; the US Treasury rate and the domestic credit obtained from the International Monetary Fund’s International Financial Statistics (IFS 2008 CD ROM). Lack of consistent monthly data over the entire sample period makes it difficult to include Qatar and the United Arab Emirates in the present study.
To assess the distributional properties of the data, Table (1) assembles some summary statistics for the above mentioned selected variables. As can be noted from the table, the Omani market registered the highest monthly returns of 0.39%, followed by the returns of Saudi Arabia’s market, 0.36%, and Kuwait’s market, 0.29%. The lowest monthly return in the four countries belongs to Bahrain’s market at 0.25%. The Saudi market exhibits the highest degree of risk as measured by the standard deviation (3.5% per month) and the Bahraini market is the least risky with standard deviation of only about half (2%) of Saudi’s market. Skewness, as a measure of asymmetry of the series around its mean, shows that the distributions of all variables in the four countries are almost symmetrical. The kurtosis statistics provide a measure of thickness of the tails of a distribution relative to normal distribution. The kurtosis far exceeds three across the variables suggesting that the empirical distribution has more weight in the tails and leptokurtic (peaked). These market characteristics are consistent with those found by Bekaert and Harvey (2000) for emerging markets.

The Table presents some descriptive statistics for the variables used in our estimation. Variables are INDEX, OIL, INT, and DC, indicating stock price index, oil prices, short-term interest rate, and domestic credit respectively. From the stock price index series we calculate the stock returns as \(100 \times \frac{P_t}{P_{t-1}}\), where \(P_t\) is the value of stock price index at time \(t\). Monthly data are used for the period 1994:10 to 2007:12 for Kuwait, Bahrain, and Oman and for the period 1996:1 to 2007:12 for Saudi Arabia.

### Table 1: Descriptive Statistics

<table>
<thead>
<tr>
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<th>Mean</th>
<th>Median</th>
<th>Std. dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>KUWAIT</strong></td>
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</tr>
<tr>
<td>INDEX</td>
<td>0.296</td>
<td>0.509</td>
<td>2.581</td>
<td>-2.583</td>
<td>21.74</td>
</tr>
</tbody>
</table>

12 In 2006, Oman’s stock market was the only GCC market to have registered positive return (up by 14.5%).
Table (2) provides an outline of the relationship between the stock price index and the selected variables for each country. The correlation matrix among the selected variables reveals that the index is positively correlated with oil prices in the four countries. The correlation coefficients between the index and oil prices are .75, .75, .88, and .70 in Kuwait, Saudi Arabia, Bahrain, and Oman respectively. Also, the domestic liquidity in the economy is positively correlated to the index in the four countries ranging from about .4 in Oman to .87 in Bahrain. Furthermore, consistent with the theoretical background, the correlation between the interest rate and the index appears negative for Kuwait (-.52), Saudi Arabia (-.22), and Bahrain (-.03), while it appears positive (.20) for Oman. Further discussion about the relationship between stock price index and the above mentioned variables will be presented in the following sections.

The Table presents the correlation coefficients for the variables used in our estimation. Variables are INDEX, OIL, INT, and DC, indicating stock price index, oil prices, short-term interest rate,

<table>
<thead>
<tr>
<th></th>
<th>INDEX</th>
<th>OIL</th>
<th>INT</th>
<th>DC</th>
</tr>
</thead>
<tbody>
<tr>
<td>OIL</td>
<td>0.439</td>
<td>0.515</td>
<td>2.673</td>
<td>-0.021</td>
</tr>
<tr>
<td>INT</td>
<td>-0.006</td>
<td>0.015</td>
<td>0.188</td>
<td>-1.209</td>
</tr>
<tr>
<td>DC</td>
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<td>3.870</td>
<td>21.6</td>
<td>0.755</td>
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**SAUDI ARABIA**

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<tr>
<td>OIL</td>
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<td>0.515</td>
<td>2.673</td>
<td>-0.021</td>
</tr>
<tr>
<td>INT</td>
<td>-0.006</td>
<td>0.015</td>
<td>0.188</td>
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<tr>
<td>DC</td>
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**BAHRAIN**

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<td>INDEX</td>
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<td>2.673</td>
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</tr>
<tr>
<td>INT</td>
<td>-0.006</td>
<td>0.015</td>
<td>0.188</td>
<td>-1.209</td>
</tr>
<tr>
<td>DC</td>
<td>20.32</td>
<td>20.85</td>
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**OMAN**

<table>
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<th>INT</th>
<th>DC</th>
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</thead>
<tbody>
<tr>
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<td>0.240</td>
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<tr>
<td>OIL</td>
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<td>2.673</td>
<td>-0.021</td>
</tr>
<tr>
<td>INT</td>
<td>-0.006</td>
<td>0.015</td>
<td>0.188</td>
<td>-1.209</td>
</tr>
<tr>
<td>DC</td>
<td>20.04</td>
<td>16.53</td>
<td>89.85</td>
<td>0.643</td>
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</table>
and domestic credit respectively. Monthly data are used for the period 1994:10 to 2007:12 for Kuwait, Bahrain, and Oman and for the period 1996:1 to 2007:12 for Saudi Arabia.

Table 2: Correlation among variables

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<thead>
<tr>
<th>KUWAIT:</th>
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<th>INT</th>
<th>DC</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
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<tr>
<td>OIL</td>
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<td>DC</td>
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<table>
<thead>
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<th>OIL</th>
<th>INT</th>
<th>DC</th>
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<tbody>
<tr>
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<td></td>
</tr>
<tr>
<td>OIL</td>
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<tr>
<td>INT</td>
<td>-.226</td>
<td>-.041</td>
<td>1.00</td>
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<tr>
<td>DC</td>
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<td>.635</td>
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<table>
<thead>
<tr>
<th>BAHRAIN:</th>
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<th>OIL</th>
<th>INT</th>
<th>DC</th>
</tr>
</thead>
<tbody>
<tr>
<td>INDEX</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OIL</td>
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<td></td>
</tr>
<tr>
<td>INT</td>
<td>-.030</td>
<td>-.134</td>
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<tr>
<td>DC</td>
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<td>.919</td>
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<td>1.00</td>
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<table>
<thead>
<tr>
<th>OMAN:</th>
<th>INDEX</th>
<th>OIL</th>
<th>INT</th>
<th>DC</th>
</tr>
</thead>
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<tr>
<td>INDEX</td>
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<tr>
<td>OIL</td>
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<tr>
<td>INT</td>
<td>.207</td>
<td>-.121</td>
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<tr>
<td>DC</td>
<td>.392</td>
<td>.732</td>
<td>-.455</td>
<td>1.00</td>
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</tbody>
</table>

IV. THE EMPIRICAL RESULTS

This section applies the methodology described above to empirically investigate the dynamic interactions between the stock prices and the macroeconomic variables in four GCC stock markets. The main focus of our analysis is on testing for the existence of long-run equilibrium relationship between the above mentioned variables and stock prices in the context of four GCC
countries, investigating the nature of the causal relation among variables which are considered with particular attention on the causal effects they may have on stock prices and to what extent shocks in macroeconomic variables influence the stock index.

IV.i Test Results for Unit Roots

In testing for unit roots, this study employs the well-known Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests. These tests are performed on both the level variables and their first differences, with the null hypothesis being that the variable under investigation has a unit root against the alternative that it does not. If the calculate statistics is higher than McKinnon's critical value then we do not reject $H_0$ and the considered variable is non-stationary, if not it is stationary. In each case the lag length is chosen by minimising the Akaike Information Criterion (AIC). We also test for the existence of up-to-the-twelfth order serial correlation in the residuals of each regression using the Ljung-Box Q statistics. The result of these tests indicates the absence of serial correlation.

Table (3) presents the results of unit root tests for the variables in level and first differences (with trend and without trend). All variables have been transformed to natural log before the analysis. The results indicate that the null hypothesis that the level variables contain unit roots cannot be rejected by both tests for the four countries. However, after differencing the data once, both tests reject the null hypothesis. Since the data appear to be stationary in first differences, no further tests are performed. Up to this stage, we can say that the ADF and PP test statistics suggest that the four variables are candidates for cointegration.

The Table presents the results for unit roots test. ADF is the Augmented Dickey-Fuller test and PP is the Phillips-Perron test. Variables are INDEX, OIL, INT, and DC, indicating stock prices index, oil prices, short-term interest rate, and domestic credit respectively. Monthly data are used
for the period 1994:10 to 2007:12 for Kuwait, Bahrain and Oman and for the period 1996:1 to 2007:12 for Saudi Arabia. All variables are in natural log. The lag selection is based on the lowest value for Akaike Information Criterion (AIC). The null hypothesis is that the series is I(1). The critical values for rejection are: -3.4422 at 1%, -2.8798 at 5%, and -2.5766 at 10% for models without linear trend and -4.0179 at 1%, -3.1288 at 5% and -3.1437 at 10% for models with linear trend. These values are based on Mackinnon (1996) provided by Eviews. (*) indicates significant at 1% for both models.

**Table 3: Test Results for Unit Roots**

<table>
<thead>
<tr>
<th>KUWAIT:</th>
<th>Variables</th>
<th>ADF Test</th>
<th>PP Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td></td>
<td>Constant, no trend</td>
<td>Constant, trend</td>
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<tr>
<td>INDEX</td>
<td>-.5495</td>
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<td>-.6551</td>
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<tr>
<td>OIL</td>
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<td>-1.823</td>
<td>.0729</td>
</tr>
<tr>
<td>INT</td>
<td>-1.801</td>
<td>-2.448</td>
<td>-1.311</td>
</tr>
<tr>
<td>DC</td>
<td>-.6056</td>
<td>-1.912</td>
<td>-.5119</td>
</tr>
<tr>
<td>1st Diff.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INT</td>
<td>-3.820*</td>
<td>-3.8675*</td>
<td>-7.390*</td>
</tr>
<tr>
<td>DC</td>
<td>-7.956*</td>
<td>-14.004*</td>
<td>-13.869*</td>
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</table>

<table>
<thead>
<tr>
<th>SAUDIA ARABIA:</th>
<th>Variables</th>
<th>ADF Test</th>
<th>PP Test</th>
</tr>
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<tbody>
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<td>Level</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>OIL</td>
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<td>.0729</td>
</tr>
<tr>
<td>INT</td>
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<td>-2.448</td>
<td>-1.311</td>
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<tr>
<td>1st Diff.</td>
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<td></td>
</tr>
<tr>
<td>INT</td>
<td>-3.820*</td>
<td>-3.8675*</td>
<td>-7.390*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BAHRAIN:</th>
<th>Variables</th>
<th>ADF Test</th>
<th>PP Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INDEX</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OIL</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC</td>
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</tr>
<tr>
<td>Level</td>
<td>INDEX</td>
<td>OIL</td>
<td>INT</td>
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<td>-------</td>
<td>-----</td>
<td>-----</td>
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<tr>
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<td>.0729</td>
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<tr>
<td>INT</td>
<td>-1.801</td>
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<th>INT</th>
<th>DC</th>
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</thead>
<tbody>
<tr>
<td>INT</td>
<td>-3.820*</td>
<td>-3.8675*</td>
<td>-7.390*</td>
<td>-7.410*</td>
</tr>
<tr>
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**OMAN:**

<table>
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<tr>
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<th>DC</th>
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<th>INT</th>
<th>DC</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-6.521*</td>
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<td>-11.421*</td>
</tr>
<tr>
<td>INT</td>
<td>-3.820*</td>
<td>-3.8675*</td>
<td>-7.390*</td>
<td>-7.410*</td>
</tr>
</tbody>
</table>

**IV.ii Test Results for Cointegration**

Since all the variables included in the model pertain to stationary time series data, there exists the possibility that they share a long-run equilibrium relationship. To test this, we apply the multivariate cointegration test, Johansen's test (1991). The Johansen method provides two different likelihood ratio tests: the trace test statistic and the maximal Eigen value test statistic to determine the number of cointegrating vectors. Before applying the Johansen method to estimate the parameters of the cointegrating relationship and the adjustment coefficients $\beta$ and $\alpha$, it is necessary to determine the lag length (k) to be included in the VAR equation (1). The lag length should be high enough to ensure that the errors are approximately white noise, but small enough...
to allow estimation. We select the optimal lag length according to several different criteria. The
criteria include the sequentially modified Likelihood Ratio (LR) test, Final Prediction Error
(FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan
Quinn Information Criterion (HQ). We select the optimal lag length based on the most common
lags resulting from those criteria. Three out of five criteria, the LR, FPE, and AIC, show that two
lags are appropriate in the case of Kuwait, Saudi Arabia, and Bahrain and three lags in the case of
Oman. The results of testing the number of cointegrating vectors are reported in Table (4). As
can be seen in all four countries, both the trace test and the maximum Eigen value statistics yield
identical results. They are both sufficiently large to reject the null hypothesis of no cointegration
among the variables in the four countries (only the trace test is significant in the case of Oman).
Specifically both tests suggest the existence of a unique cointegrating vector linking together the
four variables in the four markets over the long run.

The result that stock price index cointegrates with the remaining variables in the model means
that its movement toward a long-run equilibrium state defined by the cointegrating equation
characterizes its long-run behavior. Therefore, in the short run, any deviation of the stock prices
from this long-run equilibrium will feed back on their changes in order to force their movement
toward their long-run equilibrium state. The coefficient of the cointegrating vector in the stock
prices equation is the adjustment coefficient of stock prices and measures their speed of
adjustment to the long-run equilibrium state. The adjustment coefficients of stock prices are
small and significant for Kuwait, Saudi Arabia, and Bahrain, but insignificant for Oman. As
illustrated in Table 5, (α) is .08, .08, .07 for Kuwait, Saudi Arabia, and Bahrain and means that
in each short-term period, for example, Kuwait stock prices adjust by about 8% of the imbalance
that exists at time (t-1) between its current value and its long-run equilibrium value given by the
long-run equilibrium relationship. However, consistent with Hassan (2003), the coefficient on the cointegrating vector in the index of Oman appears small and insignificant, which may reflect the exogeneity of Oman’s stock price index.

After normalizing the coefficients of stock price indices to one, the restricted long-run relationship between stock prices and macroeconomic variables for the four countries can be expressed as:

Kuwait Index = .049 OIL - .290 INT + .667 DC
   [.0488]  [-5.263]  [14.515]

Saudi Arabia Index = .350 OIL -.113 INT + .746 DC
   [2.511]  [-1.451]  [8.499]

Bahrain Index = -.691 OIL + .356 INT + .649 DC
   [-3.256]  [4.540]  [2.641]

Oman Index = -2.079 OIL + .711 INT -3.168 DC
   [-4.053]  [5.66]  [-4.464]

The t-statistics in [ ].

Before interpreting the results, it is important to emphasize here that the above estimated coefficients relate only to the long-run relationship. That is, the estimated coefficients can be viewed as describing some trend linking between the variables concerned. Also, these estimated long-run coefficients may be interpreted as elasticity measures since the variables are expressed in natural logarithms.

As expected, the oil price factor appears positive and significant for Saudi Arabia. Consistent with Hammoudeh and Choi (2006), the results reveal the existence of long-run relationship between the stock price index and oil prices. This is as anticipated and not a surprising result for the Saudi Arabia case which has the highest percentage of oil revenues to total revenues (about 90% in 2005) among GCC countries. Consequently, in the case of Saudi Arabia, it is expected that an
increase in oil prices (oil revenues) will boost not only the local business activities directly linked to oil, but also other businesses through its impact on government revenues and public expenditure on infrastructure and other mega projects. Furthermore, it seems that the surge in oil revenues in the last few years has fueled an economic boom that has created many profitable business opportunities for private firms and consequently reflected in their performance and stock prices.

However, in the case of Kuwait, the oil prices do not show statistically significant relationship with the price index, while negative and significant coefficients appear for Bahrain and Oman. The reasons for these results vary across countries. In Kuwait, the market is highly sensitive to fads and herding (Hammoudeh and Choi, 2006), and that makes the monthly connection between oil prices and stock market weak. The Kuwaiti result should not mean that Kuwait’s stock market is not sensitive to oil price changes in the long run, but it may be that this market is more sensitive to other changes in other variables, such as liquidity in the economy and interest rate (as evident from the above Kuwaiti results), and thus corporate profits are related, but indirectly, to oil revenues. Thus, it seems that the loop is too long for changes in oil prices to be reflected by the stock price index. For the case of Bahrain and Oman, the negative and significant coefficients of oil prices can be explained by the fact that since the increase in oil prices is expected to raise the production cost in industrial oil importing countries, then an increase in oil prices is expected to raise the cost of imported capital goods, therefore adversely affecting the prospects of higher corporate profits in these markets.

Norwegian and Indonesian stock markets, the short-term interest rate appears with negative and significant coefficients in the case of Kuwait. The negative effect of interest rate is very evident from the perspective of stock valuation models, where interest rates are considered as discount factors. The Kuwaiti result indicates that in this country the short-term interest rate represents alternative investment opportunities. As the interest rate rises, investors prefer to switch out of stocks, causing stock prices to fall and vice versa. However, the insignificant coefficient of Saudi Arabia may refer to application of Islamic Shari’a considerations which play a role in weakening the effect of the interest rate on investment. Also, this result can be explained by the fact that despite Saudi Arabia following the fixed exchange rate with the US dollar, the risk premium for its currency varies over time and weakens the linkage.

In the case of Bahrain and Oman, the coefficients appear positive and significant. It is known that interest rates can be used by the central banks as a growth stimulus instrument. Thus, decreasing interest rates might indicate a central bank response to an economic downturn, and rising interest rates might be a response to an economic upturn. Therefore, the positive coefficient in the case of Bahrain and Oman can be explained by counter-cycle central bank responses to economic fluctuations.

Consistent with Mukherjee and Naka (1995) for the Japanese market; Cheung and Ng (1998) for Canada, Germany, Italy, the US, and Japan; and Kwon and Shin (1999) for Korea, the results reveal a positive and significant long-run relationship between the index and domestic credit in the case of Kuwait, Saudi Arabia, and Bahrain. Conversely, the domestic credit in Oman negatively and significantly influences stock price performance. As we discussed before, the relation between domestic liquidity and stock index can be positive or negative. Higher domestic

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13 According to the Islamic Shari’a, interests on investments are prohibited. The basic principle of Shari’a is the sharing of profit and loss (Murabahah) on investments.

liquidity can increase future cash flows, corporate profitability, and thereby raise the stock prices, while the opposite outcome is likely to happen in recession.

So far, we can conclude that monthly stock prices, oil price, short-term interest rates and domestic liquidity are cointegrated with one cointegrating vector in all the four countries, which indicates the existence of a stable, long-term equilibrium relationship among these variables. These results are consistent with Chaudhuri and Koo (2001) who investigate the volatility of stock prices in some Asian emerging markets. They find that both domestic and international macroeconomic factors have a significant relation with stock price volatility. Also, the results are consistent with Nasseh and Strauss (2000) who find a significant long-run relationship between stock prices and domestic and international economic activity in France, Germany, Italy, the Netherlands, and the UK. Furthermore, the results show that the stock price indices in Kuwait, Saudi Arabia, and Bahrain are adjusting to the long-term equilibrium states, whereas prices in Oman are not. Again, we need to emphasize here that the above estimated coefficients related only to the long-run relationship. That is, the estimated coefficients can be viewed as describing some trend linking the variables concerned. They, however, do not tell us about the short-term relationship and the dynamic interactions among the variables. Accordingly, we proceed with testing the causality relation, variance decomposition and impulse response function based on VAR specification.

The Table presents the cointegration test. Variables are INDEX, OIL, INT, and DC, indicating stock prices index, oil prices, short-term interest rate, and domestic credit respectively. r represents the number of cointegration vectors. (**) and (*) indicate rejection of the null hypothesis at 1% and 5% level of significance respectively.
Table 4: Johansen cointegration tests

<table>
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<tr>
<th></th>
<th>Critical value</th>
<th>Max Eigen value</th>
<th>Trace test</th>
<th>Critical value</th>
<th>Null</th>
<th>Alternative</th>
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<tr>
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<td>23.80</td>
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<td>54.07**</td>
<td>39.89</td>
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<td>11.44</td>
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<tr>
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<tr>
<td>BAHRAIN</td>
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<tr>
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</tr>
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<td>3.84</td>
<td>6.51</td>
<td>3.340</td>
<td>3.84</td>
</tr>
</tbody>
</table>

Variables are INDEX, OIL, INT, and DC indicating stock prices index, oil prices, short-term interest rate and domestic credit respectively. $\beta$ is the matrix of cointegrating vectors, $\alpha$ is the speed of adjustment coefficients. t-statistics in [ ].
Table 5: The $\beta$ and $\alpha$ vectors from the restricted model

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
<th>$\alpha$</th>
</tr>
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<tbody>
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</tr>
<tr>
<td>INDEX</td>
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</tr>
<tr>
<td></td>
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<tr>
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<tr>
<td></td>
<td>[0.488]</td>
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</tr>
<tr>
<td>INT</td>
<td>-0.2902</td>
<td>-</td>
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<tr>
<td></td>
<td>[-5.263]</td>
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<tr>
<td>DC</td>
<td>0.6671</td>
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<tr>
<td></td>
<td>[14.51]</td>
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</tr>
<tr>
<td><strong>SAUDI ARABIA</strong></td>
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<td></td>
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<tr>
<td>INDEX</td>
<td>1</td>
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<td>[-3.300]</td>
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<tr>
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<td>[2.511]</td>
<td></td>
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<tr>
<td>INT</td>
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<td>-</td>
</tr>
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<td></td>
<td>[-1.451]</td>
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<tr>
<td>DC</td>
<td>0.7465</td>
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<td>[8.499]</td>
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</tr>
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<td><strong>BAHRAIN</strong></td>
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<tr>
<td>INDEX</td>
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<tr>
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<td>[-2.933]</td>
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<tr>
<td>OIL</td>
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<td>[-3.256]</td>
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<tr>
<td>INT</td>
<td>0.3569</td>
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<td>[4.540]</td>
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<tr>
<td>DC</td>
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<td>-</td>
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<td><strong>OMAN</strong></td>
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<td>INDEX</td>
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<tr>
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<td>[-1.295]</td>
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IV.iii Test Results for Granger Causality Analysis

Before testing for Granger Causality Analysis, and since the results are sensitive to departures from the standard assumptions, we subject the residuals of the estimated VECM equations to a battery of diagnostic tests. The results suggest that the residuals pass the tests at 95%. In particular, the Lagrange multiplier test statistics indicate no serial correlation among the residuals for each country. In addition, Ljung-Box Q-statistics (not reported) indicate no autocorrelation.

Given that the analysis of the causal relation focuses on the short-term dynamics of stock prices in Kuwait, Saudi Arabia, Bahrain, and Oman, and how their short-run behavior is affected by the other variables in the system, we focus our attention on testing for the existence of Granger Causality Analysis in only one direction: from oil prices, short-term interest rate and domestic credit to stock prices. The existence of such causality means that past information on oil prices, short-term interest rate and domestic credit help predict future values of stock prices in those countries. The Granger Causality Analysis results appear in Table (6). The results vary from country to country and appear to be mixed. Generally, it is evident that economic activity represented by the three variables Granger-causes stock prices in the four countries. The results suggest that stock prices in Kuwait are being significantly Granger-caused by both oil prices and domestic credit, while the stock index in Saudi Arabia Granger-caused by the three factors: oil prices, short-term interest rate, and domestic credit. In Bahrain, the stock prices index is affected

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>OIL</td>
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<td>INT</td>
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<td></td>
<td>0.7117</td>
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<td>DC</td>
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<tr>
<td></td>
<td>-3.1689</td>
<td>[-4.464]</td>
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</tbody>
</table>


only by the short-term interest rate, while in Oman the index is affected by both oil prices and short-term interest rate.

It is useful to remember here that the Granger Causality Analysis tests the existence of short-term causal relation from one variable to another, while the cointegration test in the previous section tests the long-term equilibrium relationship among the variables. Specifically, the results of the Granger Causality Analysis suggest that stock prices in Kuwait, Saudi Arabia and Oman are being significantly Granger-caused by oil price. However, no such relation is registered for Bahrain. These results are consistent with what we discussed earlier that despite the fact that the GCC economies depend to a large extent on oil revenues, they individually have different degrees of oil dependency.

These results mean that, in the short term, stock prices in Kuwait, Saudi Arabia, and Oman are sensitive to oil price changes. This is an understandable result since oil exports in these countries determine their foreign earnings and their government budget revenues and spending. Thus, they primarily determine the aggregate demand which influences the corporate activities, earnings and stock prices. However, the result of Bahrain is not surprising as Bahrain is not a major oil exporter and it depends on Saudi Arabia for financial aid. For example, Bahrain has the lowest oil dependency rate measured by the oil sector as ratio of GDP (about 23% in 2005) among the GCC countries.

Similarly, domestic credit appears to have a significant causal effect on the stock prices in Kuwait and Saudi Arabia in the short run; however, no causal effect is observed from domestic liquidity to the index in Bahrain and Oman. The results of Bahrain and Oman are consistent with Bhattachraya and Mukherjee (2002) for the Indian stock market. In addition, consistent with Hammoudeh and Choi (2006), the stock price index of Saudi Arabia, Bahrain, and Oman appear
to be mainly driven by the short-term interest rate (proxied by the US Treasury bill rate) in the short run. This makes sense since the present value model suggests that prices are determined by the future cash flows and the discount rate for those cash flows. However, there is not such a causal impact for Kuwait.

Clearly, the Granger Causality Analysis results brought out the importance of oil price in affecting the stock price movement. These results are consistent with Achsani and Strohe (2002) for Norway and Indonesia; Jones and Kaul (1996) for the US, Canada, and Japan; and Papapertou (2001) for Greece. The results indicate that our economic argument is valid for GCC countries included in the sample. In particular, oil prices do profoundly impact the stock market in both the short and long run. This indicates the importance of oil prices in determining stock prices in an oil-dependent economy like those of the GCC countries. Furthermore, Granger Causality Analysis illustrates an important result which is consistent with the fact that although all GCC countries rely heavily on oil exports for revenues, their macroeconomic environments are mostly different. This result is not surprising, considering the difference in the structure of the economies of these countries, including the degree of economic diversity, the direction of economic policies, and the current stage of economic and financial development.

Generally, the results suggest that the historical values of economic activity, more or less, can predict current and future stock price movement in Kuwait, Saudi Arabia, Bahrain, and Oman. This evidence suggests that the value of the stock price index in the four countries functions of past and current values of macroeconomic variables since they constitute the information set used to generate a flow of expected future income. Furthermore, the statistical significance of causal relations verifies the fundamental and theoretical linkages between stock prices and macroeconomic variables in the four GCC countries. Although the empirical evidence related to
developing economies is limited, our results are found to be consistent with some of the studies done on the developed economies. For example, the predictive power of economic factors over the stock prices is also observed by Dhakal, Kandil, and Sharma (1993), Abdullah and Hayworth (1993), and Pesaran and Timmermann (1995) among others.

IV.iv Test Results for Variance Decomposition and Impulse Response Functions

The precise interpretation of the VAR model can be brought out through the generalized variance decomposition analysis and the estimation of the generalized impulse response functions to investigate the dynamic properties of the system. In what follows, we examine the generalized variance decomposition and the generalized impulse response functions among the variables in order to gain insight into the following question: to what extent do shocks in macroeconomic variables influence the stock index?

The Table presents the Granger Causality Analysis. Variables are INDEX, OIL, INT, and DC, indicating stock prices index, oil prices, short-term interest rate and domestic credit respectively. (***) , (**) and (*) indicate 10%, 5% and 1% level of significance respectively.

**Table 6: Causality Tests**

<table>
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<th>Null Hypothesis</th>
<th>F-Statistic</th>
<th>Probability</th>
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<tr>
<td>OIL does not Granger Cause INDEX</td>
<td>2.28537</td>
<td>0.10524***</td>
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<tr>
<td>INT does not Granger Cause INDEX</td>
<td>1.58764</td>
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<td>DC does not Granger Cause INDEX</td>
<td>3.91968</td>
<td>0.02199*</td>
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<td><strong>SAUDI ARABIA</strong></td>
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<td></td>
</tr>
<tr>
<td>OIL does not Granger Cause INDEX</td>
<td>4.37223</td>
<td>0.01443*</td>
</tr>
<tr>
<td>INT does not Granger Cause INDEX</td>
<td>4.50455</td>
<td>0.01277*</td>
</tr>
<tr>
<td>DC does not Granger Cause INDEX</td>
<td>4.55833</td>
<td>0.01216*</td>
</tr>
<tr>
<td><strong>BAHRAIN</strong></td>
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<td></td>
</tr>
<tr>
<td>OIL does not Granger Cause INDEX</td>
<td>1.62538</td>
<td>0.18593</td>
</tr>
<tr>
<td>INT does not Granger Cause INDEX</td>
<td>2.70382</td>
<td>0.04765*</td>
</tr>
<tr>
<td>DC does not Granger Cause INDEX</td>
<td>0.77216</td>
<td>0.51137</td>
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</table>
The decomposition of the forecast error variance of stock prices due to shocks in macroeconomic variables is reported in Table (7). The reported numbers indicate the percentage of the forecast error in the index that can be attributed to innovations in other variables at five different time horizons: one month, six months, one year ahead (short-run), eighteen months, and two years ahead (medium to long-run).

The results of generalized variance decomposition analysis and the generalized impulse response functions provide more or less the same conclusion regardless of the order of decomposition since their estimation is independent of the order. The analysis of the generalized variance decompositions tends to suggest that the index in each country in this empirical analysis can be explained by the disturbances in macroeconomic variables. Not surprisingly, at short horizons, the variances in all four countries’ stock prices are mainly attributed to the index itself. However, the effect drops as the horizon lengthens. At the two-year horizon, the portion of the forecast error variance explained by the index itself remains large in Bahrain (92%), Saudi Arabia (70%) and Oman (63%), but about the half in Kuwait (55%).

Looking through the main diagonal, we may ascertain the extent to which a variable is exogenous since this represents how much of a market variance is being explained by a movement in its own shock over the forecast horizon. Statistically, if the variable explains most of its own shocks, it does not allow variances of other variables to contribute to it being explained and it is therefore said to be relatively exogenous. The most endogenous one is the Kuwaiti market, in the sense that the variability in the index allows being explained by the other variables in the model. At the
one-year horizon, 5% of the variability in the index is explained by innovations in oil prices, 2% by short-run interest rate, and 7% by domestic liquidity. However, these percentages increase as time lengthens. At the two-year horizon, 15% of the variability in the price index is explained by innovations in oil prices, 10% by innovations in short-term interest rate, and about 21% by innovations in domestic credit. This implies that past information on short-term interest rates and domestic credit together explain about 31% of the future changes in the stock prices in Kuwait, while the largest part of the change is due to past (historical) information on the stock prices themselves.

For Saudi Arabia, at the two-year horizon, about 11% of the variations in the price index are explained by innovations in oil prices, 10% by short-term interest rates, and 9% by domestic liquidity. However, the oil price and short-term interest rate innovations together explain about 7% of the variation in index in Bahrain. As indicated in Table (7), changes in oil prices are the main contributor to changes in stock prices in Oman; about 28% of the variation in the price index is explained by oil price shock at the two-year horizon. Moreover, for Oman, about 8% of the forecast error variance of index can be equally split between short-term interest rates and domestic credit.

While the oil price innovation explains almost 14% and 11% of the variation in the index in Kuwait and Saudi Arabia, it explains about 30% of the variation in the price index in Oman. Those three markets are relatively more sensitive to shocks coming from oil prices. The short-term interest rate innovation has the largest effect in Kuwait and Saudi Arabia, and it has the smallest in Bahrain and Oman. Generally, while much of the variation in the price index of the four countries can be attributed to their own variations, we note the prominent role of macroeconomic variables in forecasting variances of stock prices; this is consistent with Nasseh
and Strauss (2000) who claim that a significant fraction of stock price variance is explained by real economic activity for six OECD countries.

An alternative way to obtain information about the relationship among the four variables included in the variance decomposition analysis is through the generalized response function to one standard error shock. Figure (1) shows the impulse response functions analysis for a horizon of two years illustrating the response of the stock price to a one standard deviation shock to all macroeconomic variables in each country. The impulse response analysis shows that all the macroeconomic variables are important in explaining stock prices’ movement. In general, the impulse response functions appear to be consistent with the results obtained from the VECM and the variance decompositions discussed above. The index shows positive response to shocks from oil prices which leads to about 5%, 4%, 2%, 11% changes in the index for Kuwait, Saudi Arabia, Bahrain, and Oman respectively over two years. In addition, the index responds negatively to interest rate shocks. Particularly, shocks from interest rates force the market down by 4%, 6%, 5%, and 5% in Kuwait, Saudi Arabia, Bahrain, and Oman respectively over two years.

The innovation analyses suggest that the GCC stock markets interact with their own key macroeconomic factors. Most of the variations in the index can be captured by innovations in oil prices, short-term interest rates and domestic credit. The causal relationships - that the macroeconomic variables Granger-cause stock prices - are quantitatively supported by the innovation analyses. Also, the innovation analyses reveal that all four GCC stock markets are driven by their macroeconomic variables providing further evidence concerning the causal relationships between macroeconomic variables and stock prices in these countries. The oil positive shock will benefit all GCC markets. Positive short-term interest rate shock has a negative effect on Kuwaiti and Saudi markets, but a neutral or positive effect for Bahrain and
Oman. This may refer to the fact that some GCC countries have tied their currencies more closely to the US dollar than others.

Interestingly, across the various methodologies, the results reveal the importance of the oil prices in affecting the stock prices’ indices in the context of GCC countries. Therefore, we conclude that in the GCC an oil price bust can cause fluctuations in stock prices. This conclusion is consistent with what one expects in countries in which oil revenues are the main source of national income. Thus, oil revenues become the major determinant of the level of economic activity and the mechanism by which the government can affect the circular flow of income within the economy including stock market prices.

The Table presents the decomposition of the forecast error variance of stock prices due to shocks in macroeconomic variables. Variables are INDEX, OIL, INT, and DC, indicating stock prices index, oil prices, short-term interest rate, and domestic credit respectively. The reported numbers indicate the percentage of the forecast error in the index that can be attributed to innovations in the index itself and other variables at five different time horizons: one month, six months, one year ahead (short-run), eighteen months, and two years ahead (medium to long-run).

Table 7: Generalized Variance Decompositions

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<th>Period</th>
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<th>OIL Shock</th>
<th>INT Shock</th>
<th>DC Shock</th>
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<td>0.000000</td>
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<td>54.66874</td>
<td>14.79788</td>
<td>9.982315</td>
<td>20.55106</td>
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</table>

SAUDI ARABIA INDEX
V. SUMMARY AND CONCLUSION

Using a recent set of monthly data covering the period 1994:10 – 2007:12, this paper investigates the relationship between stock prices and main macroeconomic variables (i.e. oil prices, short-term interest rate, and domestic credit) that are believed to affect stock prices in the context of the GCC markets. For this purpose, this paper employed recent time series techniques of cointegration and Granger Causality Analysis. While Granger Causality Analysis tests the short-run influence of one variable on the other, the multivariate cointegration technique tests the long-run relationship among the variables. In addition, to have an idea about the relative importance of the variables in predicting the future values of stock prices, we decompose the forecast error variance of stock prices into components accounted for by innovations in the different variables
These procedures enable us to evaluate the percentage of stock prices’ forecast error variance attributable to macroeconomic shocks. While the variance decomposition indicates the percentage of a variable’s forecast error variance attributable to innovations in all variables considered, the impulse response functions capture the direction of response of a variable to a one standard deviation shock to another variable. Accordingly, the dynamics that exist among these variables may be fully addressed.

The multivariate cointegration tests identified that oil prices, interest rates (proxy by the US Treasury bill rate), and domestic credit have long-term equilibrium effects on stock market prices in the four GCC countries. We find that these factors form a cointegrating relationship with stock prices in these countries. In addition, the Granger Causality Analysis highlighted that the causality is running from oil prices to the stock price index in the case of Kuwait, Saudi Arabia, and Oman. Also, the causal flow from the domestic credit to the index has been found in the case of Kuwait and Saudi Arabia, while the interest rate has a causal effect on the stock price index in the case of Saudi Arabia, Bahrain, and Oman. Generally, our findings are consistent with those of Mukherjee and Naka (1995), Kwon, Shin and Bacon (1997), Cheung and Ng (1998), Nasseh and Strauss (2000), who examine the impact of several macroeconomic variables on stock markets in both developed and emerging economies and find that macroeconomic variables have a significant impact on the stock market and/or the existence of a long-run relationship between these macroeconomic variables and stock prices.

Further assessment of the relationship between these variables, based on generalized variance decomposition and generalized impulse response functions, reveals the importance of oil prices in explaining a significant part of the forecast error variance of the index in Kuwait, Saudi Arabia, and Oman. The generalized impulse response functions led us to conclude that oil price
shocks do have an important and significant impact on the stock price index in the four countries. The results suggest that oil price fluctuations account for a major and significant influence within the system constructed. Furthermore, the innovation analyses tend to suggest that the GCC stock markets dynamically interact with their own key macroeconomic factors. Most of the variations in the stock prices can be captured by innovations in the three selected variables. Therefore, the causal relationship - that the macroeconomic variables Granger-caused stock prices - is quantitatively supported by innovation analysis.

The fact that our results show that both global and local macroeconomic factors affect the performance of the stock prices in the GCC markets has important implications. Since these markets are closed and restricted to the locals only, one would expect, a priori, that these markets are insulated and not well-integrated with global financial markets. However, our results show that even though they are closed markets, they are influenced by and integrated with world events. On the basis of our findings, domestic markets are influenced through oil prices and the US Treasury bill rate, and factors are determined by world related fundamentals. These factors influence the domestic economic environment of the GCCs and through this effect feed their impact on the GCC stock markets. Thus, even if the stock markets are closed to the outside world, the fact that the domestic economic fundamentals are driven by world events means that the stock markets themselves are integrated with and influenced by events and volatility shocks in the global economy. Finally, this line of research could be enhanced by considering more macroeconomic variables such as GCC stock markets fundamentals and by the inclusion of social and political factors used as dummy variables on these grounds. However, this is beyond the aim of this paper, and it is left for future research.
References


The Overrating of Financial Expectations at the Origin of the Crisis: An Evaluation using the Dempster-Shafer Credibility Function

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Abstract

This article is contextualized within the phenomenon of new financial instruments surfacing on the international economic scene, which has led to the emergence of speculative practices, credit expansion and the so-called stock market boom, which in turn has led to instability and the crisis that we are currently experiencing. An analysis of the possible causes that have prompted the emergence of the "illusion" that speculative financial transactions could generate profits without any risk is the starting point for this study, in which the Dempster-Shafer Theory is applied in order to establish a theoretical framework that might enable us to analyze the making of decisions with incomplete information and to quantify the credibility that investors give to information sources when it comes to the decision to buy sub-prime mortgage-backed securities.

KEY WORDS: Crisis; uncertainty; approximate reasoning; Dempster-Shafer; Credibility

JEL CLASSIFICATION: C15; D81; E17

I. INTRODUCTION

In the 2009 report by the Working Group of the UNCTAD secretariat (United Nations Conference on Trade and Development) on systemic issues and economic cooperation, its Secretary General made a repeated call for stricter international monetary and financial governance, considering that the dynamics of the crisis are the result of failures in domestic and international financial deregulation, persistent global imbalances, the lack of an international monetary system and the deep inconsistencies that exist between global trade, financial and monetary policies.
One of the triggers of the crisis that we are now experiencing has been the phenomenon of speculation and wastefulness that have occurred under the cover of a blind faith in the efficiency of deregulated financial markets and the lack of a financial and monetary system based on cooperation. The belief that speculative financial transactions in many areas could yield in profits without risk and granted a license for taking a gamble has been the catalyst for the creation of many speculative bubbles for some products, which have since popped after the commotion of high-risk or *sub-prime* mortgages.

This article is contextualized within the moment of growth of the speculative phenomenon in the international financial markets to develop the application of a methodology that enables us to analyze the circumstances in which investors have carried out the process of making decisions to invest in mortgage-backed securities that are characterized by a certain lack of transparency. This methodology, based on the application of the Dempster-Shafer theory, will enable us to distinguish between uncertainty and ignorance due to incomplete information, in addition to enabling us to calculate the credibility that investors attribute to the information that they use, in order to ultimately determine how alterations in this parameter (credibility) occur, which involves the emergence of doubt or ignorance regarding the accumulation of evidence or the surfacing of new evidence.

II. **The Practices of Speculative Investment: An Analysis of its Causes and Consequences**

In recent years, the international economic stage has witnessed a significant growth in the emergence and purchasing of financial products such as derivatives, hedge funds, pension funds, etc. The proliferation of speculative practices in the trading of these products, combined with a strong credit expansion and the so-called stock market booms, have led to instability in the international financial markets.
The search for attractive investment options outside of the productive sphere, under the cover of financial deregulation and liberalization, has led to financial speculation, and consequently, the rise in the price of assets in the capital markets. More favorable financial conditions, of profitability and liquidity, as well as the increase in credit availability, caused banks and other financial institutions to go ahead and grant credit for speculative practices, given the expected and desired profit to be gained. The banks assumed high-risk approaches by providing funding for non-production activities, which had no livelihood assets or flow of income that guaranteed repayment of the loans granted, which placed the financial markets and the economy in a position of high vulnerability. In addition, the credit was channeled more so to mortgages and to consumption than towards the production sector. They granted more loans than were allowed by the existing deposits they had to abide by them.

The boom of the mortgage sector relied on the greater demand for housing as a result of the increased availability of credit granted by the bank, and the low interest rates, as well as the proliferation of the purchase and sale of securities (securitization\textsuperscript{15}) backed by home mortgages that were acquired by international banks. A good portion of the massive supply of mortgages were granted to families that hardly had enough income to pay them when the interest rates were very low, and consequently, when the interest rates started to climb and the mortgages became more and more expensive, this led to payment default. This situation immediately affected the banks that had granted these mortgages, given that they had also sold the mortgage-backed securities in the financial markets (whereby they not only receive the money that they lent plus interest, but they also obtain a profit from negotiating the credit instruments). In this manner, the crisis started to expand to other sectors, although, given the nature of the financial markets,

\textsuperscript{15} The term \textit{securitization} is derived from \textit{securities}, given that it is in the Capital Markets.
which are based mainly on elements of credibility, integrity and confidence, the detrimental consequences of the financial crisis may be more devastating and persistent that those caused by similar episodes in other markets or productive areas.

III. Investment Decisions Based On Inaccurate Information: The Monetary Illusion that Triggered The Financial Crisis

Right in the middle of the Great Depression, John Maynard Keynes published his General Theory of Employment, Interest and Money [1936], and from this point forward the Keynesian principles about the role that the fiscal and monetary policy represents for fighting against recession became fully integrated into the ideology of economists, politicians and part of the general public. According to the Keynesian approach, the economy is not governed solely by rational stakeholders who, “like an invisible hand”, desire to undertake business activities aimed at obtaining a mutual economic profit, as the traditional economists believed. Keynes came to realize that although the majority of the economic activities tend to have rational motivations, there are also many other activities that are governed by animal spirits, which explains the underlying instabilities in capitalism. The use of the term spiritus animalis, which comes from medieval Latin, is what served as the title and inspiration for a recent book in which its authors, the economists George A. Akerlof (Nobel prize in 2001) and Robert J. Shiller, consider a series of psychological variables that have been overlooked in the conventional economic analysis. Such would be the “animal spirits” [2009], which uses the word animal to represent mental energy and vital force. There are five animal spirits that the authors consider to be influential in

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16 According to the economics dictionary of The Economist, “animal spirits” is “the peculiar name that Keynes gave to one of the essential ingredients for economic prosperity: confidence. According to Keynes, the animal spirits are a sort of confidence or “candid optimism.” By that, he meant that for entrepreneurs in particular, “the thought of ultimate loss which often overtakes pioneers—as experience undoubtedly tells us and them—is put aside as a healthy man puts aside the expectation of death.”

economic decisions: confidence, equity, corruption and anti-social behavior, monetary illusion, and the love of stories. The fluctuation of our confidence was one of the most probable causes of the current financial crisis; that is, the confidence, or the excess of confidence, that the property that one is about to buy or sell will be worth more within one year. Equity also appears as an animal spirit, influencing thousands of decisions in ways that differ from the standard theory. Due to a sense of equity, for example, bosses often pay their employees’ higher wages than what the market demands. “The considerations of equity are a great motivating force behind many economic decisions” writes Akerlof-Shiller, “and they are related to our sense of confidence and our ability to work together effectively. Corruption is also an animal spirit.” That includes the tendency to produce not only what people really need, but also what they think they need, such as insurance policies backed by mortgage, “a modern version of snake oil,” the authors declare.

In their list of animal spirits, the two economists place special emphasis on the tendency of people to think in narrative terms or in terms of stories. “A lot of confidence tends to be associated with inspiring stories, stories about new business initiatives, stories of how other people got rich,” write the authors. A good part of the explanation of the reason for this crisis lies in the “illusion” that speculative financial transactions in several areas could yield profits without risk and they granted a license for taking a gamble. This “illusion” has been fueled by the blind faith in the efficiency of deregulated financial markets and the lack of a financial and monetary system based on cooperation (according to the words of the Secretary of the UNCTAD).

In a global economy where financial capital circulates very quickly and changes hands often, and offers highly sophisticated and automated financial products, not all investors (whether a
financial institution, a bank or a private individual) know the ultimate nature of the transaction they have entered into or the actual risk assumed.

The problem emerged when the evidence was confirmed that major banking institutions and large investment funds had placed their assets in high-risk mortgages, which caused a sudden shrinkage of credit (a phenomenon known as a *credit crunch*) and an enormous volatility in stock market values, creating a downward spiral of a lack of confidence combined with investment panic, and a sudden drop in stock markets across the globe, particularly due to the lack of liquidity.

In sum, the main problem lies in the fact that when making their decisions, investors were acting based on incomplete or inaccurate information (something that as human beings, we often do in our daily lives) and got carried away by that “illusion” of unlimited profit, which combined with the fluctuating and inconsistent component of the economy (thus related with the ambiguity or lack of certainty), caused an inaccurate assessment of the risks, whether intentionally or not, which was amplified by the automation of the stock market, the misinformation of private investors and the unprecedented liquidity during the 2001-2007 period.

Having analyzed the causes that motivated the investors who made risky decisions, overrating expectations and using incomplete information in the majority of cases, and after arriving at the conclusion that prior knowledge is not the only factor that explained investor behavior, we decided to approach this work based on the Dempster-Shafer theory, which will help us to better understand the environment in which this set of financial investment decisions were made, and at the same time, it will give us more insight in order to perform an in-depth study about how people vary the degree of cognitive effort that they devote to processing persuasive messages.
about unlimited earnings, placing other justifications that are closer to the “animal spirit” before their ability to make rational decisions (with complete or almost complete information).

This theory has shown to be an alternative method of reasoning that can be used in situations where the strict requirements of theoretical probability cannot be met, when ignorance must be modeled explicitly, or when the evidence involves a set of possible confusing events instead of having a direct answer. The proposal is the creation of an additional source of information that helps to better understand a real and complex problem, the uncertainty associated with it and the objectives to be achieved, and that offers recommendations about the steps to be taken.

IV. **Dempster-Shafer Theory of Evidence**

The human ability to rely on qualitative evidence when making decisions under uncertainty is astonishing efficient. Default reasoning simulates the qualitative nature of human reasoning, enabling the jump to conclusions as the basis of the way of thinking. That is why, according to the Prospect Theory by Ricardo Pascale [2008]^{18}, “the function of value of an economic decision must not be calculated by weighing the probabilities, but rather by a weight function that measures the impact of the events on the desirability of the prospective and not simply the perceived probability of the events.” When we enter into the realm of uncertainty, there is not even the slightest possibility of establishing any law of probability; that is, there is no Bayesian probability.

The Dempster-Shafer Theory has to do with the ambiguity of information, and provides a great variety of measures that give more accurate information about the type of uncertainty found in data. Thus, one distinguishes between uncertainty and ignorance. Instead of calculating the probability of a proposition, it calculates the probability that there is evidence that justifies the proposition. This measurement of belief is known as a belief function. The systems based on this

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theory use probability intervals to get a certain idea about the need for evidence or not. The probability interval represents the difference between the “probability, given the existing evidence” and the “maximum probability obtainable when there is additional evidence.” The theory of evidence has been widely applied in various fields, such as the combination of evidence of diverse sources for support in making decisions and the creation of an expert system for this purpose, the combination of image data to eliminate uncertainty in medical applications, the discovery of information in databases, and the analysis of image data with uncertainty, etc.

For the description of the methodology on which the Dempster-Shafer Theory is based, we will place ourselves in the context in which lenders and investors buy and sell securities that were originated directly by the lenders in the mortgage market and that have security or backing in these loans.

In the practical development that we will explain, we present a simulation of the decision to buy securities backed by a mortgage loan. The investors (institutional investors, wealthy individuals and the very savings institutions) have been attracted by the liquidity and diversification. Given that the key for channeling high-risk mortgage debt through the market will consist of dividing the risk, investment-grade tranches that carry little risk are created as well as higher-risk tranches with a lower grade in which the investor should position himself. The problem is that many of the securities that offer high profitability are not transparent and the investors must have confidence exclusively in the backing-solvency of whoever creates them or sells them, and in the case of investors with a less risky profile, who rely on the rating given by the rating agencies, they give credibility to this fact as it may be the case that the rating agencies themselves have incomplete information when issuing their ratings.
Let us start with three investor profiles that made the decision to buy based on a set of hypotheses $D$ created based on the information available, expectations, or confidence in the credibility of the seller. The universal set of decisions $D$ can be based on $\{\text{ratings published (A), profitability offered (B), estimated risks (C), credibility of the issuer (D), credibility of the seller (E), opinion based on experience of others (F)}\}$.

1. **Institutional investors (i1):** Their exposure to risk is moderate and their decisions are based primarily on the opinion of the rating agency, which plays a vital role as it gives an opinion about the risk associated with the quality of the asset to be securitized. Their measurement of certainty of this information is 0.6 for the fulfillment of the hypotheses $\{A, B$ and $C\}$.

2. **Deposit institutions (Banks) (i2):** Their exposure to risk is moderate. Their decisions are also based on the rating of risk issued by rating agencies (their measurement of certainty is 0.7 for the fulfillment of the hypotheses $\{B, C, D, E\}$), they pursue profitability, but they are mainly interested in taking over the assets that remain on the balance sheet of the institutions in a securitized form, and that can be used as security when applying for funding from the Central European Bank (CEB).

3. **Private individual (i3):** Their exposure to risk is medium-high. Their objective is to obtain high profits and they confide in the solvency-credibility of the issuer of the security. They give this information a measure of certainty of 0.8 for the fulfillment of the hypotheses $\{D, E, F\}$, although they know that there is a certain lack of transparency in the security; that is, their information about what they are buying is not complete.

We will use the theory of sets to abbreviate and represent the entities in the most abstract manner. The set of decisions of the first investor profile considered (institutional investor) will have been made by considering the pieces of information corresponding to $A$ (ratings published), $B$ (profitability offered), $C$ (credibility of the issuer), if we compare it with investor $i2$ (banking
institution), we can determine the measures of probability associated with the intersection of hypothesis on which their decision is based. We will consider the intersections $i_1 \cap i_2$ (table 1), $i_1 \cap i_3$ (table 2), $i_2 \cap i_3$ (table 3) and finally, $i_1 \cap i_2 \cap i_3$ (table 4):

\[
i_1 \times i_2
\]

\begin{array}{c|cc}
| & D & 1: i_1 \cap i_2 = \{B,C\} \quad 0.6*0.7=0.42 \\
| i_2 & 0.6 & 0.4 \\
| i_1 & 0.7 & 1 \\
| D & 3 & 4 \\
| & 0.3 & 0.3*0.4=0.12 \\
\end{array}

Table 1

The results obtained indicate the degree to which the investors $i_1$ and $i_2$ do not question the information they receive. Thus, the 0.42 indicates the degree to which the investors $i_1$ and $i_2$ do not question the usefulness provided by the information indicated as B and C.

\[
i_1 \times i_3
\]

\begin{array}{c|cc}
| & D & 1: i_1 \cap i_3 = \{A,B,C\} \quad 0.3*0.6=0.18 \\
| i_1 & 0.6 & 0.4 \\
| & 0.3 & 0.3*0.4=0.12 \\
\end{array}
Note that the expert assigns a value to the empty set, which means that he contemplates the possibility that a statement not specified in the domain could be significant in the decision-making process.

### Table 2

<table>
<thead>
<tr>
<th>i3</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
</table>
| 0.8 | D | i3 = { } 19
| 0.48 |

\[ 0.6 \times 0.8 = 0.48 \]

2: \[ i3 \cap D = \{ C, D, E, F \} \]

\[ 0.8 \times 0.4 = 0.32 \]

\[ \text{0.32} \]

\[ \text{0.61} \]

3: \[ D \cap i1 = \{ A, B, C \} \]

\[ 0.2 \times 0.6 = 0.12 \]

\[ \text{0.12} \]

\[ \text{0.23} \]

4: \[ D \cap D = \{ A, B, C, D, E, F \} \]

\[ 0.2 \times 0.4 = 0.08 \]

\[ \frac{0.08}{1 - 0.48} = 0.15 \]

When coming up with an empty set as a result, we must subtract the complement from the probability in the remaining boxes.
With Dempster’s rule, the focal sets of i1 intersect with i2, i2 with i3, and i1 with i3, and finally, i1 with i2 and i3, obtaining a new potential with the combined basic assignments. Because the chosen focal area is small, there are only a few intersections found, obtaining their values by simple multiplication.

\[ i_1 \times i_2 \times i_3 \]
<table>
<thead>
<tr>
<th></th>
<th>i2</th>
<th>i1</th>
<th>( i3 )</th>
<th>( \cap )</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.28</td>
<td>0.18</td>
<td></td>
<td>3, 4</td>
<td>0.33</td>
</tr>
<tr>
<td>2</td>
<td>{B, C} ( \cap ) D</td>
<td>0.42*0.2=0.08</td>
<td>[ \frac{0.08}{1-(0.33+0.14)} ]</td>
<td>= 0.15</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>i2 ( \cap ) i3={B,C,D,E}</td>
<td>0.28*0.8=0.22</td>
<td>[ \frac{0.22}{1-0.47} ]</td>
<td>= 0.41</td>
<td></td>
</tr>
</tbody>
</table>

4: \( i2 \cap D \) 0.28*0.2=0.05 \[ \frac{0.05}{1-0.47} \] = 0.09

---

Table 4

<table>
<thead>
<tr>
<th></th>
<th>i1 ( \cap ) i3={B,C,D,E}</th>
<th>i1 ( \cap ) D={A,B,C}</th>
<th>D ( \cap ) i3={C,D,E,F}</th>
<th>D ( \cap ) D={A, B, C, D, E, F}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.18*0.8=0.14</td>
<td>0.18*0.2=0.03</td>
<td>0.12*0.8=0.096</td>
<td>0.12*0.2=0.02</td>
</tr>
<tr>
<td>2</td>
<td>0.18*0.2=0.03</td>
<td>[ \frac{0.03}{1-0.47} ] = 0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.12*0.8=0.096</td>
<td>[ \frac{0.096}{1-0.47} ] = 0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.12*0.2=0.02</td>
<td>[ \frac{0.02}{1-0.47} ] = 0.03</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
With the previous data, we now calculate the Credibility and Plausibility. The credibility refers to the degree of confidence that is given to a piece of information; plausibility, at first glance, reasonably implies a realization, although there is an allusion to the possibility of being wrong:

**Credibility granted by the investors i1 and i2 to the information represented by the values \{B, C, D\}:**

\[ \text{Cr} (i1 \times i2) = \{B, C, D\} \]
\[ \{B, C\} \cap \{B, C, D\} \neq \{B, C, D\} = 0 \]
\[ i2 \cap \{B, C, D\} = \{B, C, D\} = 0.28 \]
\[ i1 \cap \{B, C, D\} \neq \{B, C, D\} = 0 \]
\[ D \cap \{B, C, D\} = \{B, C, D\} = 0.12 \]

Thus, Credibility (i1 x i2) with respect to \{A, B, C\} = 0.28 + 0.12 = **0.40**

**Plausibility granted by the investors i1 and i2 to the information represented by the values \{B, C, D\}:**

\[ \{B, C\} \cap \{B\} = \{B\} \]
\[ \{B, C\} \cap \{C\} = \{C\} \]
\[ \{B, C\} \cap \{D\} \neq \{D\} \]
\[ i2 \cap \{B\} = \{B\} \]
\[ i2 \cap \{C\} = \{C\} \]
\[ i2 \cap \{D\} = \{D\} \]
\[ i1 \cap \{B\} = \{B\} \]
\[ i1 \cap \{C\} = \{C\} \]
\[ i1 \cap \{D\} \neq \{D\} \]
\[ 0.42 + 0.28 + 0.18 + 0.12 = 1 \]
The institutional investors $i_1$ and $i_2$ grant the maximum plausibility to the information represented by B, C, D, although investor $i_1$ believes that if it made the decision based on the information represented by the variable D (credibility of the seller), there would be the possibility of being wrong. According to the Dempster-Shafer Theory of Evidence, the difference between credibility and plausibility is a measure of the uncertainty. Thus, when credibility and plausibility are equal, there is absolute certainty about the impact of evidence on the hypotheses considered. When credibility is 0 and plausibility is 1, the difference between both measurements is maximum, and thus, we do not know anything about the impact of the evidence on the hypotheses considered. When the values of credibility and plausibility are different, the greater the difference between them, the greater the uncertainty about the impact of the evidence on the hypotheses considered.

Next, we will calculate the intervals of belief, first starting with the values of doubt (the degree of doubt is what is lacking in the degree of plausibility for the whole) and values of plausibility or credibility (Table 5):

<table>
<thead>
<tr>
<th>Values of doubt</th>
<th>0.82</th>
<th>0.72</th>
<th>1</th>
<th>0.58</th>
<th>1</th>
<th>1</th>
<th>0.88</th>
</tr>
</thead>
<tbody>
<tr>
<td>Values of plausibility</td>
<td>0.18</td>
<td>0.28</td>
<td>0</td>
<td>0.42</td>
<td>0</td>
<td>0</td>
<td>0.12</td>
</tr>
<tr>
<td>or credibility</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5
The left end of each interval corresponds to the value of belief of each investor or of the whole, and the right end corresponds to the plausibility of the whole. It is observed that the investor designated by i3 (private investor) whose decisions were made based on information that is not very well verified, based exclusively on opinions and comments received and the image of credibility offered by the issuer or seller of the security, is that which presents a higher percentage of uncertainty or doubt, and the criteria for choosing their investments differs substantially from the criteria followed by the other investor profiles selected, the institutional investor and the financial institution.

The financial institution (i2) is that which presents a lesser degree of uncertainty in its decisions with respect to the other investor profiles. It has more information than i1 (institutional entity), given that its decision is made based on the ratings offered by the rating agencies, and knowledge of the banking sector. Therefore, it can more carefully evaluate the solvency or security offered by the bank issuing the mortgage-backed security that it is purchasing.
The institutions can rectify their belief values and send them to the nodes that provided evidence. This will be implemented by successive decision processes; thus, in this manner, if the investors were to discover that the information that they had relied on to make their decision was malicious or wrong, they would automatically reformulate their belief values. This fact makes Dempster's rule significant, which also enables calculating the degree of contradiction between two pieces of evidence defined on the framework of discernment.

V. CONCLUSIONS

In the problem presented in this article, we describe a clear situation where investor agents face situations in which they must make decisions based on uncertain or incomplete data. Traditionally, the lack of information has been considered to be an undesirable and detrimental situation for making decisions. The practical potential of the theoretical framework proposed, known as the Dempster-Shafer Theory of Evidence, offers advantages insofar as it enables distinguishing between ignorance (difference between plausibility and credibility) and uncertainty, thus making it possible to manage a valuable piece of information about the structure of the problem, which in turn will enable a deeper and more complete analysis than that which could be obtained by traditional procedures based on the theory of probability. However, this theoretical approach has several disadvantages that are now being researched, such as its computational complexity, for instance.

The Dempster-Shafer Theory of Evidence proposes a repetitive process for evaluating the impact on the hypotheses of successive evidence. In this manner, belief in the hypotheses initially put forward is combined with that acquired in the following repetition when evaluating the impact of a new piece of evidence. For this reason, it is a very valuable method when the relationships of
cause and effect are not clear, and therefore require non-explicit or observable knowledge for making the decision.

References


The combination of forecasts: An application of a time-varying simple weighting method to inflation forecasts in Turkey

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Abstract

We present a study on combining the forecasts from a time-series model and an econometric model in the context of the inflation rates of Turkey and propose a new weighting scheme, the time-varying simple weighting method. Our guiding principle for the deduction of this method is based on retaining the practicability and straightforwardness of simple averaging while avoiding the data-driven aspects of time-varying approaches. We further provide a topical and qualitative overview on the exhaustive literature of forecast combinations and apply our newly developed combination method to test for the prospective credibility of the inflation-targeting regime of the central bank of the Republic of Turkey.

Keywords: Forecast combination, Combination weights; Autoregressive Moving Average, Time Series; Forecast, Forecasting, Econometric modeling; Consumer Price Index, CPI, Inflation;

JEL classification: C32; C53; E37; E31;

1. INTRODUCTION

In order to combine two or more individual forecast into one meaningful final forecast, appropriate weighting is a sine qua non condition and hence deserves all the attention of the researcher. In this regard, extending the notion of parsimony into the domain of forecast combination one ultimately seeks a framework that inhabits a simple perspicuous structure for practical purposes and yet retains a certain dimension of complexity for theoretic attraction. A model generated by these guidelines constitutes a sophisticated model, which bears the potential to be appealing to both practitioners and theoreticians alike. In line with this notion, the quest for sophistication within the field of forecast combination can be reduced to one focal point, and that
is the weighting scheme.

Impedingly, there is no consensual agreement upon the scientific community on what constitutes a proper weighting scheme. It seems as if the choice of the weighting functions, and hence the proper combination of the individual forecasts, is highly contextual with a large element of arbitrariness and subjectiveness. As a consequence to these aggravations, the derivation of clear guidelines or rules for choosing the correct combination technique is not straightforward. For our purposes, as it turns out, one anchor point lends us guidance for the appropriate choice of a weighting scheme, namely the temporal virtues of our forecast models, which is a seasonally autoregressive moving average (SARIMA) model and a new Keynesian Phillips curve (NKPC) model. Speaking in the figurative sense, our proposed weighting scheme can be viewed as the manifestation of the temporal merits of our models, ergo the advantages of one model over the other for different time horizons. In essence, we can incorporate these temporal aspects into the weighting scheme of our combinations by assigning the short-term SARIMA forecast more weight for the short run and allocating the medium-term NKPC more weight for the medium run. As a result we propose a new weighting function that enables the integration of the favorable short-term characteristics of a time-series model with a simultaneous implementation of a medium to long-term econometric model.

Our study offers added value on three fronts to the existing literature. First, we provide a methodological approach for combining two distinct forecast models from two separate fields of forecasting, time-series and econometrics, in the context of Turkish inflation rates and extend the concept of simple linear weighting to the non-linear domain. Second, we present an up to date qualitative overview on the comprehensive literature of forecast combinations. Third, motivated by the outcomes of our forecast combination approach, we offer a practical policy evaluation of
the current inflation-targeting regime of the central bank of the Republic of Turkey and its prospective consequences in view of the European integration of Turkey. All in all, the conjunction of the methodology, the application and the emerging market problem context of Turkey constitute a unique advance in the field of forecast combinations.

The remainder of this paper is organized as follows. Section I gives an introduction to the forecast combination paradigm and an overview on the existing literature and the various combination methods. In Section II we delve into the many advantages and disadvantages of forecast combinations. Section III provides the main results of our proposed time-varying simple weighting methodology within the context of forecasting the inflation rates in Turkey. And lastly, section IV gives a conclusion to the study and an outlook for future research.

I. The forecast combination paradigm

The seminal paper that literally founded the domain of forecast combination was first published by (Bates and Granger 1969). They initially make their case by showing that simple equal weighting of two separate forecasts startlingly reduces the variance of the errors. Motivated by this initial result, they propose combination techniques that take the errors of the individual forecasts into account and enable to assign more (less) weight to the individual forecast that possesses a higher (lower) degree of accuracy. By doing so, reference is made to the relative performance of the individual forecasts and to the interdependencies via the calculation of the covariances and correlations of the forecast errors.

The fundamental notion for an optimal combination, hence weighting scheme, is developed under the following rationale. First, Bates and Granger assume that the individual forecasts are stationary processes so that the error variances are time-invariant. Secondly, they assume that the individual forecasts are unbiased, and if not initially, corrected for the bias to attain this
condition. It is essential that none of the individual forecasts is biased since combining could amplify the bias even further when all individual forecasts are biased or lead to higher error variances compared to the unbiased individual forecast when only one individual forecast is biased. *Thirdly*, the individual forecasts must possess a certain degree of independent information in order to render the combination worthwhile.

Presuming that these conditions are met, the unbiased combined forecast can be expressed by a linear combination of two individual forecasts:

\[ C_T = k_T f_{1,T} + (1 - k_T) f_{2,T} \]  

where \( k \) and \( 1-k \) are the weights and \( f_{1,T} \) and \( f_{2,T} \) the respective individual forecasts at time \( T \). The error variance of the combined forecast is given by:

\[ \sigma_C^2 = k^2 \sigma_1^2 + (1-k)^2 \sigma_2^2 + 2\rho k \sigma_1 (1-k) \sigma_2 \]  

where \( \sigma_1^2 \) and \( \sigma_2^2 \) are the respective error variances of the individual forecasts and \( \rho \) the correlation coefficient between the errors of the individual forecasts. The combined variance equation can be reformulated as a minimization problem, where the optimal weight \( k \) has to be chosen accordingly to minimize the combined variance \( \sigma_C^2 \). In consequence, differentiating the combined variance equation with respect to \( k \), setting it to zero and rearranging derives the **optimal weight**:

\[ k = \frac{\sigma_1^2 - \rho \sigma_1 \sigma_2}{\sigma_1^2 - \sigma_2^2 - 2\rho \sigma_1 \sigma_2} \]

Assuming that the individual forecasts are independent, and thus not correlated with each other, the correlation coefficient \( \rho \) equals zero and the optimal weight that minimizes the combined variance reduces to:
Both formulations ensure that the weight \( k \) is chosen optimally so that the combined variance is equal to or less than the smaller of the individual variances ((Bates and Granger 1969), p.453). As is apparent, the calculation of the optimal weight \( k \) is directly related to the correlation coefficient and hence to the variance-covariance structure of the errors. This is reflected by the term \( \rho \sigma_1 \sigma_2 \), which is arithmetically equal to the error covariance \( \text{cov}(\sigma_1, \sigma_2) \). In wake of this, a problem that arises is that the covariance matrix is not known in practice and must be estimated via a consistent and efficient method. Since any estimation under a finite sample size incurs some sampling variability, those sampling errors could in consequence inhibit the estimation of optimal weights as envisioned in above (Dickinson 1973; Diebold and Lopez 1996). Empirical evidence suggests that this is not commonplace and that the optimal method performs reasonably well in a variety of circumstances (e.g. (Bunn 1985)), however, in conceptual terms it is still considered to be the Achilles’ heel of the optimal weighting scheme.

Based on the above rationale, Bates and Granger propose five methods and show empirically, by using forecasts on international airline passenger data, that combining successfully reduces the overall mean-square error in comparison to the individual forecasts.

After Bates and Granger’s groundbreaking work, an extensive body of literature has been published over the course of the last 40 years. There were close to 600 publications on the topic of forecast combination up until 1998 alone (Trenkel and Götz 1998). A good review on the developments and broad bibliographical references are provided by (Clemen 1989; Granger 1989; Trenkel and Götz 1998; de Menezes, Bunn et al. 2000; Wallis 2008).

Several weighting and combination schemes have been proposed in the forecast combination literature and can be broadly categorized into: Simple average weighting, optimal weighting,
regression weighting, information criteria weighting and new weighting methods.

1. Simple average weighting

The equal weighting of the forecasts was the starting point of the argumentation of (Bates and Granger 1969) for using forecast combinations. A simple average weighting scheme takes the following form:

\[ f_{c.t} = \sum_{j=1}^{k} \frac{1}{k} f_{j.t} \]  

where \( f_{c.t} \) is the combined overall forecast, \( \frac{1}{k} \) the equal weights and \( f_{j.t} \) the individual forecasts.

Over the years, simple averaging has been popular among researchers due to its favorable properties, such as robustness and ease of implementation. In fact, the remarkable performance of equal weighting spawned a vast amount of literature on an anomaly what has come to be known as the forecast combination puzzle (Stock and Watson 2004b). It is remarkable in the sense that simple averaging repeatedly outperforms more complicated combination methods in practice and under certain conditions a combination using simple averages is expected to be more accurate than a combination using estimated weights (Smith and Wallis 2009). Smith and Wallis also provide a simple explanation for the puzzle that draws on the realization that weight estimation inevitably incurs sampling variability, which in effect could create instabilities. That brings us back to the aforementioned shortcomings of the optimal combination method. A similar explanation for the forecast combination puzzle is provided by (Issler and Lima 2009), who offer a description along the lines of the curse of dimensionality, which occurs whenever an increasing number of weights must be estimated. This in effect raises the variance of the estimated weights and thus undermines consistency. To avoid the curse of dimensionality they propose a modified equal weighting method, the bias-corrected average forecast, which is conceptually a simple equal weighting scheme with a bias correction.
Another explanation for the prevailing good performance of equal weighting is given by (Aiolfi, Capistran et al. 2010). They point to the fact of a bias-variance trade-off, where equal weighting is expected to lead to a lower error variance with more bias than more sophisticated weighting methods, which will then again be less accurate but also less biased.

Since the attention in the forecast literature lies predominantly on the accuracy of forecasts, cardinaly the mean-square-error criterion, equal weighting seems to be favored from a practical standpoint. Advocates of simple averaging are inter alia (Bessler and Brandt 1981; Makridakis, Andersen et al. 1982; Makridakis and Winkler 1983; Kang 1986; Holden and Peel 1988; Batchelor and Dua 1995; Taylor and Bunn 1999; Hendry and Clements 2002; Fang 2003; Jose and Winkler 2008; Constantini and Pappalardo 2009).

I.ii. Optimal weighting

As has been explained in above, the optimal weighting method was first proposed by Bates and Granger in their seminal work published in 1969. Under the aforementioned assumptions and derivations, the optimal method ensures that the weights are chosen accordingly to minimize the error variance of the resulting combination. Extending Bates and Granger’s original formulation from the bivariate to the multivariate case, the optimal weights can be represented by the following equation (Hansen 2008):

\[
k(m) = \frac{\tilde{\sigma}^2(m)^{-1}}{\sum_{j=1}^{M} \tilde{\sigma}^2(j)^{-1}}
\]  

As a result, the weight for each model \( m \) is constructed in inverse proportions to the forecast error variances, which is to say that a model with a higher (lower) forecast variance and hence a lower (higher) forecasting accuracy will be assigned a lower (higher) weight in the combined forecast. Again, the optimal method requires the estimation of a variance-covariance matrix, which leads to sampling errors that can weaken the consistency in the estimation of the weights.
According to (Granger and Ramanathan 1984) the optimal weighting method is equivalent to a least square regression without a constant and the sum of the weights constrained to unity. Furthermore, depending on the statistical properties of the variance-covariance matrix the optimal weighting method can be modified to overcome known issues. Two versions are prevalent, the *optimal adaptive method with independence assumption*, which restricts the variance-covariance matrix to be diagonal, and the *optimal adaptive method with restricted weights*, which restricts the weights to be in the interval 0 and 1 (de Menezes, Bunn et al. 2000).

An extension to a larger set of forecast methods and further corroborating empirical evidence for the optimal techniques are given by (Newbold and Granger 1974; Makridakis, Andersen et al. 1982; Winkler and Makridakis 1983). Proponents of the optimality approach are ((Mills and Stephenson 1985; Clemen 1986; Lobo 1991; Shen, Li et al. 2010), q.v. (de Menezes, Bunn et al. 2000)).

**Iii. Regression weighting**

This methodology draws on a simple OLS estimation in a regressional set-up where the actual values of interest are regressed on the individual forecasts and an intercept.

The regression weighting approach gained popularity among researchers because it offers favorable properties such as being simple, adaptive and yet sophisticated enough to account for certain dynamics of the weighting structure, which simple averaging cannot. The introduction of this approach into the forecast combination domain was conducted by (Granger and Ramanathan 1984), however, the idea dates back to (Crane and Crotty 1967; Reinmuth and Guerts 1979). A typical regression for a bivariate combination would look as follows:

\[ y_t = \alpha + \beta f_{1,t} + \gamma f_{2,t} + \varepsilon_t \quad (7) \]

And the extension to the multivariate case is given by simple summation:
where $y_t$ stands for the actual values at time $t$, $\alpha$ is the constant term, $\beta_i$ the respective parameters and hence combination weights, $f_{it}$ and $f_{it}$ the individual forecasts at time $t$ and $\epsilon_t$ the error term at time $t$. In general, the regression parameters are estimated by simple OLS. Other variants include predictive least squares (Hansen 2008), recursive least squares (Ravazzolo, van Dijk et al. 2007), generalized least squares (Guerrero and Pena 2003) and weighted least squares (Diebold and Pauly 1987).

One of the advantages of weighting by means of a regression is that it mitigates the problem of biased individual forecasts, and under the violation of the bias assumption of Bates and Granger it outperforms the optimal weighting method (Ibid.). Granger and Ramanathan show that under the restriction of $\alpha=0$ and $\sum \beta_i=1$ the combination of unbiased individual forecasts will result in an unbiased combination and reduce to the optimal method of Bates and Granger. The advantage of the regression approach however comes in the form of bias mitigation, that is to say that if there are biased individual forecasts, then the unrestricted regression where $\alpha$ and $\beta$ are free to vary will ensure a bias correction and lead to an unbiased forecast combination. In corollary, the constant $\alpha$ ensures bias correction and should be retained even if it is known that the individual forecasts are unbiased (q.v. (Fang 2003), p.90).

There is a large literature on regression weighting and in summary (Diebold and Lopez 1996) emphasize four notable versions: Time-varying combining, dynamic combining, non-linear combining and Bayesian shrinkage.

Time-varying combining accounts for the temporal characteristics of individual forecasts and reflects the relative performance of any forecast in the combination over time by conditionally adjusting the assigned weights. For example, an individual forecast that is expected or known to
be more accurate in the short run will receive higher weighting for the short-term and a lower weight in the long-term. Advocates of this approach are inter alia (LeSage and Magura 1992; Coulson and Robins 1993; Ravazzolo, van Dijk et al. 2007; Guidolin and Timmermann 2009).

In *dynamic combining* regressions the serial correlation of the error terms in the individual forecasts are explicitly taken into consideration in order to allow for dynamics that would otherwise be excluded. The admittance of serial correlations in the errors reflects the notion that the initial models are likely to be misspecified and that the imposition of error independence would inhibit the proper apprehension of the temporal dynamics of the forecasts. Advocates of this regression approach are (Diebold and Pauly 1987; Diebold 1988).

As the name suggests, *non-linear combining* regressions address non-linear combinations of individual forecasts by non-linear estimations of weights. A good example is given in (Diebold and Lopez 1996) in reference to (Deutsch, Granger et al. 1994), who propose a non-linear combination of forecasts by utilizing state variables that determine the combination weights by appraising the past forecast errors and other economic variables.

*Bayesian shrinkage* techniques in the context of forecast combination regressions are first proposed and investigated by (Clemen and Winkler 1986; Diebold and Pauly 1990), q.v. (Copas 1983). This methodology refers to the use of Bayesian approaches in connection with shrinkage estimation for the calculation of the weights. In general terms, prior information on the weights structure is integrated into an OLS process of weight estimation. In effect, the posterior combining weights are calculated by averaging the OLS weights and the prior weights. The combination of the prior weight information in conjunction with the OLS weight information allows for improvements in the accuracy of the weights, that is to say that the resulting weight estimates will likely lower the mean square errors of the final forecast combination. This
procedure enables the weights to “shrink” towards the arithmetic mean, hence the nomenclature *Bayesian shrinkage*.

Another method that is closely related to regression weighting is *forecast encompassing testing*. This approach refers to a simple test developed to assess whether two or more models contain the same source of information. If one model encompasses the other than the encompassed model provides redundant information and the information sources are said to be dependent and highly collinear. Any combination thereof will not yield improvements in accuracy and hence a combination should be avoided.

In essence, encompassing tests are utilized by regressing the actual value of the variable of interest on the individual forecasts and tested whether the parameter values are significantly different from zero. A typical strategy is to compute forecasts from a list of forecast models, then test for encompassing via a regression and finally select the most promising model combination for an overall forecast. Accordingly, the forecast encompassing test could be considered as a quantitative guide for the selection of an appropriate forecast combination (q.v. (Diebold 1989; Fair and Shiller 1989; Fair and Shiller 1990; Harvey, Leybourne et al. 1998; Fang 2003; Constantini and Pappalardo 2009).

Other proponents of regression-based combinations are inter alia (Holmen 1987; MacDonald and Marsh 1994; Elliott and Timmermann 2004; Smith 2009).

**I.iv. Information criterion weighting**

Another increasingly popular method for forecast combinations are *information criterion* based estimates of the weights, such as *Bayesian forecast combination*, which uses Bayesian model averaging by utilizing the BIC. Further methods include the *Akaike forecast combination*, which uses Akaike model averaging by the corresponding AIC and the *Mallows forecast combination*,


which uses the Mallows model averaging by the associated Mallows criterion (MC). Both the Bayesian and Akaike approach construct the combination weights by minimizing the respective information criteria according to a specific averaging equation (q.v. (Hansen 2008)):

\[
k(m) = \frac{\exp\left(-\frac{1}{2}BIC(m) \lor AIC(m)\right)}{\sum_{j=1}^{M}\exp\left(-\frac{1}{2}BIC(j) \lor AIC(j)\right)}
\]  

(9)

where \(k(m)\) stands for the combination weight of model \(m\) and \(BIC(m)\) and \(AIC(m)\) are the respective values for the information criteria of model \(m\) as computed by the standard formulation of \(BIC\) and \(AIC\). The exponential terms are deduced by the Bayes’ theorem.

The notion of using Bayesian model averaging as a guide for weight estimation in the domain of forecast combinations was first brought up by (Palm and Zellner 1992; Min and Zellner 1993), however, the Bayesian approach to forecast combination dates back to (Bunn 1975; Bordley 1982). A good review on Bayesian weighting is provided by (Andersson and Karlsson 2007; Eklund and Karlsson 2007) and for an excellent tutorial on Bayesian model averaging see (Hoeting, Madigan et al. 1999).

In essence, Bayesian model averaging refers to the idea of constructing a weighted average out of many competing forecast models by implementing the notion of Bayesian inference. First, a list of forecasts from various models is created and one is depicted to be the true data generating process. After that, a prior probability is attached to the presumed true model and by applying the Bayes’ rule the posterior probabilities are computed for every model. Finally, these posterior probabilities are directly translated into forecast combination weights, which are then used for pooling all obtained forecasts. Further proponents of the Bayesian approach are (Raftery, Madigan et al. 1997; Koop and Potter 2003; Raftery and Zheng 2003; Wright 2008).
The usefulness of the *Akaike* criterion in the estimation of combining weights is best illustrated in (Kolossa 2010), which also appears to be the first study specifically dedicated to Akaike based forecast combinations. In a broader sense, the interpretation of the Akaike weighting is analogous to the Bayesian weighting approach (Ibid., p.3). Another proponent of the Akaike approach is (Kapetanios, Labhard et al. 2008).

Finally, it was (Hansen 2007; Hansen 2008) who proposed the efficacies of *Mallows model averaging* and the Mallows criterion in the context of the forecasting and forecasts combination literature. The Mallows method extends the idea of Bayesian weighting to derive a more goal-oriented approach in order to overcome the inherent arbitrariness and the conceptual drawbacks of imposing certain priors on the presumed correctness of a model (Ibid., p. 342).

I.v. **New weighting methods**

Ever since the classical proposals of *Bates and Granger* and *Granger and Ramanathan* many new weighting schemes and combination strategies have been developed. Recent studies focus on novel weighting techniques such as *artificial neural network weighting* (Donaldson and Kamstra 1996; Lemke and Gabrys 2010), *controlled weighting* via quadratic programming with CUSUM and *rolling window weighting* (Chan, Witt et al. 2010), *triangular kernel weighting* (*TK*) and *inverse mean square forecast error weighting* (*IMSFE*) (Aiolfi, Capistran et al. 2010), *aggregate forecast through exponential reweighting* (*AFTER*) (Yang 2004; Zou and Yang 2004), *regime switching weighting* (Guidolin and Timmermann 2009), *discounted mean square forecast error weighting* (*DMSFE*) and *principal component forecast weighting* (Stock and Watson 2004a), *rank-ordered weighting* (Mostaghimi 1996), *logit regression weighting* (Kamstra and Kennedy 1998), *ridge regression weighting* (Clark and McCracken 2009), *odds-matrix weighting* (Gupta and Wilton 1988), *sliced inverse regression weighting* (Poncela, Rodriguez et al. 2010)
and antithetic weighting (Ridley 1997).

Besides the proposals of new weighting schemes, there are also certain suggestions for new strategies and approaches for combining, such as: four-stage conditional model combination (Aiolfi and Timmermann 2006), hierarchical forecast combination (Constantini and Pappalardo 2009) and subjective forecast combination (Maines 1996).

Traditionally, forecast estimations and combinations were solely focused on point forecasts, however, in recent years the domain has seen extensions to stochastic elements as well: volatility forecast combination via GMM (Amendola and Storti 2008), probability forecast combination (Clements and Harvey 2010) and density forecast combination (Hall and Mitchell 2007; Garratt, Mitchell et al. 2009).

II. Advantages and disadvantages of combining forecasts

Before we proceed to our own combination method we shall first depict the advantages and disadvantages of combining.

What are the main advantages of forecast combinations? First, model misspecification plays a critical role for the empirical success of combined forecasts. In general, an unintended exclusion of a relevant variable can lead to biased parameter estimates in an OLS regression. It is likely that a single forecast model is misspecified, especially when the specification of the forecast model is not guided by economic theory. In fact any model is an approximation to reality and hence per se misspecified, however, the qualifying distinction between a good model and a poor model stems from the form of the severity of the misspecification. In consequence, there is an inherent risk associated with the selection of a single forecast model, which could be a poor representation of reality and biased and thus lead to inaccurate forecasts. In view of this result, combining can be viewed as a sort of bias correction as combining two biased forecasts, e.g. via
a regression, produces unbiased composite forecasts. If two forecasting models are biased in opposite directions, then any combination will balance the biases. This point in fact led (Hibon and Evgeniou 2005) to conclude that “...the advantage of combining forecasts is not that the best possible combinations perform better than the best possible individual forecasts, but that it is less risky in practice to combine forecasts than to select an individual forecasting method.” (Ibid., p.15). In consequence, combining helps to reduce model selection uncertainty, which can be substantial in practice.

Secondly, combining different sources of information can lead to improvements in the forecasting accuracy, since any additional information lowers the forecast error variance. Closely linked to the notion of model misspecification, pooling the forecasts of different models may provide the needed information on the omitted variables, which may be excluded in one model but included in another. Under these considerations, combining forecasts reduces the risk of missing important variables with valuable information.

Third, forecast combining helps to reduce inaccuracies when location shifts in the underlying DGP occur, like in extraneous structural breaks (q.v.(Hendry and Clements 2002)).

Oddly enough, the main disadvantages of forecast combinations stem from the very advantages of it. Conceptually, forecast combinations implicitly allows for model misspecification, not to say that it even encourages it, and tries to mitigate the issue of misspecification by pooling forecasts, as has been stressed in above (q.v. (Fang 2003)). In consequence, there is a certain moral hazard involved in the endeavor to forecast combinations, that is to say that researchers might not focus on selecting the best individual forecast model, which should be their primary goal, and systematically retain many just suitable models because they implicitly foresee that forecast combining could mitigate any accuracy issue. From this perspective, a forecast
combination has the negative connotation of being a *model-mining* exercise and hence centers on quantitative aspects rather than on the more important qualitative facets of forecasting. The vast literature dedicated to forecast combinations and the increased usage of combinations in recent years seem to provide a partial evidence for this argument. However, the aforementioned *risk-reducing* argument is an indication against the *moral-hazard* line of reasoning since it is not assured that a combination increases accuracy in all circumstances, it rather helps reducing the risk of choosing a poor model. From this point of view, the critique that forecast combinations foster misspecifications and the imposed irrational behavior of the researcher becomes futile.

**III.i new forecast combination scheme for inflation forecasts in Turkey**

In consequence, comparing all the studies by the empirical findings and theoretical proposals, it becomes increasingly difficult to find guidance for deciding on a proper method. On the one hand, we have simple techniques such as equal weighting, which show positive empirical results but lack theoretical founding, and are in effect detached from any informational control on the relative performances of the individual forecasts. On the other hand, we have more sophisticated approaches such as regression weighting and optimal weighting, which provide appealing theoretical backings but seem to fail on the empirical front. This puts any researcher into the dilemma of choosing the “right” combination technique.

However, in general, some constructive advice can still be distilled from the literature. Recent studies show that the estimation of weights via optimal approaches and regressions are unlikely to lead to improvements over simple weighting methods in practice (Smith and Wallis 2009; Aiolfi, Capistran et al. 2010; Poncela, Rodriguez et al. 2010). Furthermore, the empirical ergo practical evidence pro equal weighting is stifling (q.v. (Clemen 1989) and references in above).
In virtue of these studies, we proceed to develop a simple, yet effective weighting method for our individual forecasts. Our approach consists of a *time-varying simple weighting methodology*, where the weights are conditional on the forecast horizon, similar as in the time-varying regression approach, but embedded in a more simplistic averaging framework, which is independent from the information on the performance of the individual forecasts. That is to say our approach is not data-driven, like the regression and optimal combination approach, but guided by economic theory and empirical results.

The *first motivation* for this approach comes from the results of (Nadal-De Simone 2000). They show that inflation forecasts from simple AR models perform reasonably well up until the third forecast quarter and are only markedly out-performed by a Phillips curve model in the fourth quarter. Therefore, the forecast performance of the AR model deteriorates as the horizon expands. In corollary, both models seem to provide explanatory power for different time horizons, which makes a SARIMA model especially attractive for short-run forecasts and an econometric model like the NKPC for longer forecasting horizons. Other studies also point to the temporal forecasting characteristics of econometric models and time-series models and show that a combination gives improvements over either alone (e.g. (Guerrero and Pena 2003). Guided by these findings, we propose a weighting scheme that emphasizes the SARIMA model for the short term and assigns greater weighting to the NKPC for the medium to long-term.

The *second motivation* for our approach comes from the empirical results on simple averaging. Extending the framework of simple averaging, where the weighting methodology is detached from any influence of the data, we account for the temporal characteristics of our models by declining weights rather than by equal weighting. However, just as in simple averaging, our constructed weights are not guided by the past performance of the forecasting models nor by any
estimated variance-covariance matrices and regressions. Our emphasis is rather on the simplistic
and practical scheme, which ensures that our method is easily implementable and, guided by the
evidence on the temporal characteristics, appropriately accounts for time-varying attributes.

The third important motivation comes from the literature on forecast horizons. In general, the
information content of a forecast falls in time and reaches a certain limit where the unconditional
mean becomes just as informative as or even more informative than the forecast itself. This
threshold is dubbed as the content horizon and any conditioned information contains no value
beyond that point (q.v. (Galbraith 2003)). This content horizon is going to be a valuable guide
for the depiction of our own forecasting horizon.

In a subsequent publication, (Galbraith and Tkacz 2007) provide a study on the forecast content
horizon of several US and Canadian macroeconomic variables, including the content horizon for
inflation generated by an autoregressive and a multivariate forecast model. They report that a
simple average combination of a multivariate forecast and an autoregressive forecast produces
the highest forecast content. Their graphical depictions reveal further insight into the process.
The forecast content function for the autoregressive US inflation forecast indicates flattening out
of the theoretical and empirical content curve after 12 months. Quite on the contrary, the
multivariate forecast model shows a stable structure throughout and even a slight increase in the
content after 12 months, with no significant flattening out. A simple combination of both
increases the content horizon considerably to more than 36 months, with a downward trend but
no clear demarcation where it might potentially end.

Another interesting observance of Galbraith and Tkacz is that the maximum horizons as reported
in the forecasting literature vastly exceed the computed forecast content horizons. For example,
for inflation rate forecasts the published studies indicate maximum forecast horizons of 160
months for the US and 100 months for the Euro area. The median is 24 months for the US and 64 months for the Euro area. These results suggest that many studies seem to forecast beyond the content horizon, to no avail.

These observations imply three corollaries and provide the three temporal pieces for our combined approach. First, an autoregressive forecast model seems to provide useful forecast information up until 12 months, ergo the short-term. Second, multivariate forecasting models seem to provide useful information especially beginning around 12 to 36 months, ergo the medium-term. Third, a combination extends the content horizon far beyond the content of a single model alone, even beyond 36 months, ergo the medium to long-term.

Based on this line of reasoning we propose the following weighting function:

\[ k = \frac{1}{\sqrt{t}} \]  

The bivariate combination of the individual forecasts is then expressed by:

\[ f_{ct} = k f_{SARIMA,t} + (1 - k) f_{NKPC,t} \]  

The functional form of \( k \) ensures that the weights are progressively declining conditional on time, with a rapid decline within a year when \( t \) is measured at the monthly frequency.

An illustration of our weighting scheme is provided in figure 1. Beginning from the first period, the weight begins to decline exponentially, with equal weighting attained in the fourth period \((k=0.5)\). In \( t=12 \) the weight is approximately 0.29. This weighting scheme ensures that the time-series forecasts are given more importance in the beginning of the timeline up until the fourth period. Commencing from the fourth period the econometric forecasts are gradually given more weight. This structure is just in accordance with the aforementioned empirical findings from the literature. The monthly timeline structure for our models is depicted in figure 2.

As a result, we have chosen a maximum forecast horizon of 72 months, which is reasonably close to the median forecast horizon of 64 months for Euro area studies as reported by (Galbraith
In order to quantify the improvements achieved by our approach, we will benchmark the results with simple equal weighting as well. The Turkish inflation data is obtained from the central bank of the Republic of Turkey and is of monthly frequency from 2003 to 2009. The SARIMA model is developed according to the proposed methodology in (Saz 2011a) and the NKPC model is developed as described in (Saz 2011b).20

The results of our forecast combination of the individual NKPC and SARIMA forecasts are summarized in table I. Figure 3 provides a graphical depiction of the individual and combination forecasts and the inflation targets as foreseen by the (CBRT).

Table I and figure 3 manifest salient characteristics of the outcomes. First, the NKPC forecasts exhibit a downward trend. Second, the forecasts for the SARIMA model are simple protractions of the first 12 month predictions and hence trivial in nature for longer forecast horizons. Nonetheless the predictions provide structural information on the seasonal pattern of the inflation process beyond the 12-month horizon. Third, the simple average combination provides a somewhat flat trend line and hence a slower path of declining inflation from 8.2 percent to 6.2 percent over the forecast horizon. Fourth, the time-varying simple weighting gives a closer alignment to the inflation-targeting regime of the Turkish central bank, especially after 2013. However, all targets are missed clearly by an average margin of 2.3 percentage points over the whole forecast horizon.

Table II reveals that our forecasts are much closer aligned to the IMF forecasts than to the CBRT targets with an average difference of 1.1 over the time-horizon. All in all, our forecasts compare favorable with the IMF forecasts, significantly departing only in 2011.

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20 The exact results on the SARIMA model and the NKPC model are available upon request.
In consequence to these results, the credibility of the CBRT targeting regime remains questionable for the future, particularly in hindsight of the poor performance in recent years, where inflation has been considerably off-target. Our results corroborate the poor performance of the CBRT, which was unable to create a credible targeting regime from 2006 onwards and based on our forecasts will most likely do so in the near future. The targeting scheme and the past performance is illustrated in figure 4.

Putting these results into perspective of the EU convergence measures as outlined in the Maastricht criterion on the inflation rate, several conclusions emerge. The average inflation of the three lowest CPIs plus 1.5 percent for the EU 15 from 2000 to 2010 was 2.6 percent. Using this average as the threshold for the Maastricht criterion on inflation, just as demanded in the Maastricht treaty, it becomes evident that the central bank is determined to fulfill this criterion by the end of 2015. But contrary to this plan, our results show that the inflationary goals will likely be off-target over the coming six years. This prediction can be qualitatively backed by the presumptions of public inflation expectations. Assuming that economic agents behave rationally and foresighted, any credibility gap created in the recent past will prolong into the future up until the point where the gap is closed again and hence expectations are realigned with reality. Closing the credibility gap will only be achievable by meeting the preannounced targets to a reasonably close degree, say by half a percentage point. In order to create sustainable credibility the inflation targets must be met in consecutive years. Given the uncertain current global economic conditions and given the poor inflation-targeting performance of the Turkish central bank from 2006 to 2009, the likelihood of a credible targeting over the coming years remains slim.

IV. Conclusion and outlook

In conclusion, our results indicate a sound forecast combination method that allows for a
meaningful implementation of the forecasts obtained from a time-series model like the SARIMA and an econometric model like the NKPC into a single framework. Our proposed concept for the combination of these two distinct models is a time-varying simple weighting methodology, which provides a weighting scheme that is conditional on the forecast horizon and incorporates the temporal advantages of the individual forecast models. This forecast combination method couples the advantages of simple averaging with a time-varying approach while avoiding the data-driven characteristics of the latter. Therefore, our method presents an especially important weighting scheme whenever time-series models, which are particularly regarded as informative in the short-term, are combined with econometrics models, which are known for their favorable long-term properties.

As aforementioned, a recent study on the content horizon from (Galbraith and Tkacz 2007) shows that many studies in the forecasting literature provide forecasts beyond the content horizon, which are practically trivial as they contain no additional forecast information after that point. This evidence points to the importance of the content horizon in combining distinct forecasts, and a study on implementing the concept of content horizon into a weighting scheme along our proposed methodology would prove valuable for the future research on forecast combinations.
Figures:

Figure 1: Time-varying simple weighting

Figure 2: Timeline for forecast combination of SARIMA and NKPC (in months)

Figure 3: Forecast combination graph
Figure 4: Inflation targeting of the CBRT

Source: Central bank of the Republic of Turkey

Tables:

Table I: Summary of forecast combination results

<table>
<thead>
<tr>
<th></th>
<th>NKPC</th>
<th>SARIMA</th>
<th>Simple</th>
<th>Time-varying</th>
<th>Inflation targets</th>
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<tr>
<td>2010</td>
<td>9.2</td>
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<td>8.93</td>
<td>8.94</td>
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<td>2013</td>
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<td>7.22</td>
<td>6.46</td>
<td>4*</td>
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</tr>
<tr>
<td>2014</td>
<td>5.2</td>
<td>8.32</td>
<td>6.76</td>
<td>5.61</td>
<td>3.15*</td>
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<td>2015</td>
<td>4</td>
<td>8.32</td>
<td>6.18</td>
<td>4.56</td>
<td>2.3*</td>
<td>2.3</td>
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</tbody>
</table>

*) Extrapolated by an OLS regression

Inflation targets are provided by the Central Bank of the Republic of Turkey (CBRT)

Table II: Comparison between time-varying combination forecasts and IMF forecasts

<table>
<thead>
<tr>
<th></th>
<th>Time-varying</th>
<th>IMF forecasts</th>
<th>Δ</th>
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<tbody>
<tr>
<td>2010</td>
<td>8.9</td>
<td>8.7</td>
<td>0.2</td>
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<tr>
<td>2011</td>
<td>7.8</td>
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<td>2.1</td>
</tr>
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<td>Value 1</td>
<td>Value 2</td>
<td>Value 3</td>
</tr>
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<td>------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
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<tr>
<td>2012</td>
<td>6.9</td>
<td>6</td>
<td>0.9</td>
</tr>
<tr>
<td>2013</td>
<td>6.5</td>
<td>4.8</td>
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</tr>
<tr>
<td>2014</td>
<td>5.6</td>
<td>4.3</td>
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<tr>
<td>2015</td>
<td>4.6</td>
<td>4</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Source: IMF world economic outlook, as of October 2010

References


The Effects of ‘Fear’ on Volatility- Trading Volume Relationship: Evidence from Taiwan’s Markets during the Financial Tsunami

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Abstract

In this paper, we investigate the relationship between volatility and trading volume in panic, normal, and optimistic situations in the Taiwan market during the financial tsunami. We apply the changes of Taiwan Volatility Index (TVIX) to distinguish different market emotions and Vector Autoregression (VAR) to decompose total volume into expected and unexpected volume to further explore possible different relationship. By studying the period from 2007 through 2009, including important events during the financial tsunami, we find that there is bi-directional Granger causality between total trading volume in general and volatility and asymmetric relationship between expected trading volume and volatility for different emotions. During market opening hours, market reacts to overnight emotional change. Furthermore, we find that the relationship between volatility and trading volume is not always positive. For panic and optimistic emotion, volatility does not raise total trading volume, and expected trading volume stabilizes volatility. On the other hand, unexpected trading volume raises volatility positively for panic and normal emotion. In addition to source of volatility, it implies more information content for unexpected trading volume (Lee and Rui, 2002; Speight et al., 2000). After market opening hour, overnight emotion is digested, and volatility lowers total (expected, unexpected) trading volume, while (expected, unexpected) trading volume raises volatility (Darrat et al., 2007). It is consistent with Sequential Information Arrival Hypothesis (SIAH, Copeland, 1976) if the changes of TVIX imply overnight information. Since total trading volume and unexpected volume Granger cause volatility for normal emotion, SIAH is not totally sustained.

JEL Classification: G12, G14
Keywords: TVIX; Trading volume; Volatility; Overnight emotional change
I. INTRODUCTION

The financial tsunami period during 2007 through 2008, caused considerable panic in global financial markets. For example, as the bank run on Northern Rock, Bear Stearns’ bankruptcy in 2007, Lehman Brothers was going to bankruptcy, BOA’s announcement for merger with Merrill Lynch and AIG’s request for help from FED in 2009. From America to Asia, many countries are mired in difficulties, and Taiwan is no exception. As the time difference between Taiwan and the United States, the major events happened in the U.S. market during the financial tsunami may cause panic when Taiwan’s market opened next day, and made the Taiwan Volatility Index (TVIX) raised. In this paper, we explore the relationship between volatility and trading volume in the panic and non-panic situations in the Taiwan market during the financial tsunami, and it offers us a unique chance to better understand the market reaction for ‘fear’.

In general, most studies focus on overall market transactions, and to the best of our knowledge, no extant paper researches on the overnight asymmetric reaction for investors’ emotion. Thus, this study will contribute to the empirical gap of literatures on the relationship between overnight emotional change on trading volume and volatility, and further the difference between market opening period and normal trading hours. Therefore, this study will explore for the different lead-lag relationship for different overnight emotional changes. Furthermore, we divide a trading day into market opening hour and non-market opening hours, to discuss whether overnight emotional impact on the market is all day long or not. In order to distinguish panic periods from non-panic ones, we apply the changes of TVIX (ΔTVIX) as the criteria. Besides, we apply VAR (Vector Autoregression) to decompose the total volume into expected volume and unexpected volume to explore possible different relationship between the three volumes and emotional changes.
Many extant studies examine the relationship between trading volume and volatility. Generally speaking, the relationship is predicted to be positive (e.g. Clark, 1973; Tauchen and Pitts, 1983; Harris, 1986; Epps and Epps, 1976). Furthermore, there are studies connecting trading volume and information arrival (Copeland, 1976; Karpoff, 1987; Jennings et al., 1981). Xu et al. (2005) investigate the relationship between trading volume and volatility by introducing time difference between two consecutive trades. Darrat et al. (2007) find that trading volume and volatility has dual Granger causality relationship when there is public information. However, only trading volume Granger causes volatility when there is no public information. The results are consistent with overconfidence hypothesis in behavioral finance overconfidence—overconfidence investors overestimate their private information, and their biased self-attribute makes high volatility.

Unlike traditional finance (e.g. Sharpe, 1964; Lintner, 1965; Mossin, 1966; Chen et al., 1986; Fama and French, 1992; Fama and French, 1993) which does not emphasize on investors’ emotion, behavioral finance pioneers investors behaviors since Kahneman and Tversky (1979). In behavioral finance, investors’ sentiment is one important branch. In order to observe investors’ sentiment, practitioners as well as academician propose a variety of index to measure investors’ sentiment. Direct investors sentiment indexes, summarized from surveys of investors’ views by professional institutions (e.g. American association of Individual Investors, AAII and Merrill Lynch), indirect investors sentiment indexes are criticized for fairness, credibility and publishing frequency. Thus, most studies apply direct investors sentiment indexes, which are derived from market data, to measure investors’ sentiment. Among the direct investors sentiment indexes, turnover (e.g. Conrad et al., 1994; Gervais et al., 2001; Llorente et al., 2002; Baker and Stein, 2004; Kaniel et al., 2004) and VIX (Whaley, 2000; Whaley, 2009) are two of the most popular indexes.
In this paper, we apply TVIX, which is calculated by the exact methodology of VIX, to measure investors’ sentiment in Taiwan. We anticipate positive impact for trading volume on volatility in spot market since trading volume may contain information (Copeland, 1976; Karpoff, 1987; Jennings et al., 1981). Besides, we anticipate negative impact for volatility on trading volume if investors are over confident and thus reluctant to offset their trading positions (Darrat et al., 2007). However, the relationship between trading and volatility may be different if sentiment plays an important role in trading volume. Accordingly, we hypothesize different relationships between trading volume in spot market and volatility under different sentiment, and we find that different relationships do exist, especially for market opening hour.

**Background of TWSE, TAIFEX, TAIEX, TX, and TVIX**

Taiwan Stock Exchange (TWSE) is an active exchange having huge trading volume and turnover rate in Asia. At the end of 2009, there are 741 listed companies on TWSE and the total capitalization is 657 billion USD, reaching 92.19% of Taiwan’s GDP. In that year, the trading volume is 91,364 million shares, the trading value is 92 billion USD, and the turnover is 14.01%. Compared with Tokyo Stock Exchange (TSE), the largest exchange in Asia, TWSE is relatively high in capitalization/GDP ratio (TSE: 63.28% versus TWSE: 92.19%) and in turnover rate (TSE: 9.43% versus TWSE: 14.01%). TWSE is a pure order-driven market without market makers, and the trading hours are from 9:00 to 13:30.

Taiwan Futures Exchange (TAIFEX) has become an exchange with high trading volume in the derivatives markets after 11 years of her establishment in 1998. At the end of 2009, several contracts including stock index, interest, and gold futures and options contracts are traded on TAIFEX. The number of trading accounts has grown from 75,035 in July 1998 to 1,268,199 at

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the end of 2009. Natural persons accounts for 99.38% of the total trading accounts. In 2010, the average daily trading volume is 538,349 contracts, making the yearly volume of 136,719,777 contracts. Because of the success and fast growing, TAIFEX was awarded Derivatives Exchange of the Year by Asia Risk in 2004 and 2009. Futures Industry (FIA) reports that TAIFEX is ranked as 18th large derivatives exchange with 136,719,777 contracts trading volume in 2009. The trading hours of TAIFEX are from 8:45 to 13:45 (the opening hour is 15 minutes earlier and the closing time is 15 minutes later than the spot market.)

TAIEX Futures (TX) is the most active futures contract on TAIFEX. TX is a stock index future whose underlying asset is the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). TAIEX is similar to the Standard & Poor's 500, weighted by the number of outstanding shares. TAIEX is the most widely quoted of all TWSE indices. The base year value as of 1966 was set at 100. TAIEX is adjusted in the event of new listing, de-listing and new shares offering to offset the influence on TAIEX owing to non-trading activities. TAIEX covers all of the listed stocks excluding preferred stocks, full-delivery stocks and newly listed stocks, which are listed for less than one calendar month.

In 2006, Taiwan Futures Exchange (TAIFEX) launched TVIX, which is derived from TAIEX options (TXO). The exact methodology of calculation of VIX by CBOE since 2003 is applied to calculate TVIX. Like VIX known as the investor fear gauge: the higher the TVIX, the greater the fear.

The remainder of the paper is organized as follows: Section 2 describes the sample, data and the empirical methodology. Section 4 presents the results, and Section 5 concludes.
II. DATA AND METHODOLOGY

TVIX, displayed minute-by-minute during trading hours since December 2006, is available from TAIFEX for analysis. Besides, we obtain the minute-by-minute trading price and volume data of TX and TAIEX during trading hours from TAIFEX and TWSE. The study period covers three years (January 2nd, 2007 to December 31st, 2009). This period includes bank run on Northern Rock (September 17th, 2007), Bear Stearns’ bankruptcy (July 31st, 2007), Lehman Brothers’ bankruptcy (September 15, 2008), BOA’s announcement for merger with Merrill Lynch (September 14, 2008) and AIG’s request for help from FED (September 16, 2008).

Since the Taiwan’s futures market trading hours are from 8:45 to 13:45, and the spot market trading hours are from 9:00 to 13:30, we adopt the overlap trading hours of cash and futures market, i.e. from 9:00 to 13:30. TX’s nearby contract is selected, and the criterion is consistent with TVIX- rolled over before five trading days of expiration.

The main purpose of this paper is to investigate the lead–lag relationship between volume and volatility in different market panic cases. Thus, we calculate the spot price return on minute-by-minute basis:

$$r_t = \ln \left( \frac{p_t}{p_{t-1}} \right)$$

(1)

where \(r_t\) is the spot’s price return for minute \(t\), \(p_t\) is the close price at minute \(t\), and \(p_{t-1}\) is the close price at minute \(t-1\). Although market microstructure effect may exist for the minute-by-minute data, we believe the effect is not serious because TAIEX is weighted by the number of outstanding stock shares on the TWSE and the market microstructure effect of each stock is supposed to be offset.

In addition, we apply GARCH(1,1) to estimate volatility:
\[ a_t = \sigma_t \varepsilon_t \]  

\[ \sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 a_{t-1}^2 \]  

(2)  

(3)

where \( \varepsilon_t \) is white noise, and volatility is the conditional variance estimated by Equation (3).

Similar to Illueca and Lafuente (2007), we decompose volume into predictable and unpredictable components by using a bivariate VAR.

\[
\begin{pmatrix}
v_{\text{spot}_t} \\
v_{\text{fut}_t}
\end{pmatrix} = C + \sum_{j=1}^{p} \Psi_j \begin{pmatrix}
v_{\text{spot}_{t-p}} \\
v_{\text{fut}_{t-p}}
\end{pmatrix} + U_t
\]

(4)

As Illueca and Lafuente (2007) point out, the fitted values from Equation (4) are informationless trading, and the residuals of the model are innovational trading with information.

To examine the stationary of the time series we apply Augmented Dickey-Fuller test (ADF).

Furthermore, we investigate the lead-lag relationship between volume and volatility to decompose volatility and volume by using another bivariate VAR, and then test them for Granger causality:

\[
\sigma_t^2 = \gamma_1 + \sum_{k=1}^{l} a_k \sigma_{t-k}^2 + \sum_{k=1}^{l} b_k v_{t-k} + \varepsilon_{1t}
\]

(5)

\[
v_t = \gamma_2 + \sum_{k=1}^{l} c_k v_{t-k} + \sum_{k=1}^{l} d_k \sigma_{t-k}^2 + \varepsilon_{2t}
\]

(6)

where \( v_t \) is total (expected, unexpected) volume.

The hypotheses to be tested are:

\[ H_0^1 : \sum_{k=1}^{l} b_k = 0 \quad \text{(Volume does not lead volatility), and} \]

\[ H_0^2 : \sum_{k=1}^{l} d_k = 0 \quad \text{(Volatility does not lead volume)} \]
Therefore, the results of causality test between volatility and volume are summarized as:

(a) \( H_0^1: \sum_{k=1}^{l} b_k = 0 \) and \( H_0^2: \sum_{k=1}^{l} d_k = 0 \) are not rejected. It implies that volatility and volume are independent, and there is no lead-lag relationship.

(b) \( H_0^1: \sum_{k=1}^{l} b_k = 0 \) is not rejected but \( H_0^2: \sum_{k=1}^{l} d_k = 0 \) is rejected. It implies that volatility leads volume, and volatility Granger causes volume.

(c) \( H_0^1: \sum_{k=1}^{l} b_k = 0 \) is rejected but \( H_0^2: \sum_{k=1}^{l} d_k = 0 \) is not rejected. It implies that volume leads volatility, and volume Granger causes volatility.

(d) Both \( H_0^1: \sum_{k=1}^{l} b_k = 0 \) and \( H_0^2: \sum_{k=1}^{l} d_k = 0 \) are rejected. It implies that there’s feedback relationship between volatility and volume, volume Granger causes volatility and volatility also Granger causes volume.

In this paper, we examine the intraday data with 200,366 observations. The sample is large. Therefore, we apply the critical t-value and F-value proposed by Connolly (1989) to overcome Lindley’s paradox (Lindley, 1957), which indicates that large sample tends to reject null hypotheses.

\[
t^* = \left[ (T - k)(T^{\frac{1}{2}} - 1) \right]^{\frac{1}{2}}
\]

\[
F = \left[ \frac{(T - k')}{p} \right]^{\frac{p}{T^{\frac{1}{2}} - 1}}
\]

where \( T \) is the number of observations, \( k \) is the number of parameters to be estimated under null hypothesis, \( k_0 \) is the number of parameters to be estimated under alternative hypothesis, and \( p \) is the number of restrictions \( (p = k_0 - k_1) \).

We apply the double-threshold model to the overnight change in TVIX \( (\Delta TVIX) \). That is,
\[ \Delta TVIX_t = \frac{(TVIX_t - TVIX_{t-1})}{TVIX_t} \]

The market is regarded as panic when \( \Delta TVIX \geq C_1 \), optimistic when \( \Delta TVIX \leq C_2 \), and normal when \( C_1 < \Delta TVIX < C_2 \). \( C_1 \) and \( C_2 \) are estimated according to Tsay (1998).

To overlap the trading hours for spot and futures markets, we define the time interval 9:00 to 10:00 as the market opening hour, the time interval 10:00 to 13:30 as the non-market opening hours. We do not separate market close hour because this paper focuses on the effects of overnight emotion changes.

### III. EMPIRICAL RESULTS AND DISCUSSION

First we apply ADF test to verify whether volume, price return and return volatility are stationary. As Table 1 shows, the null hypothesis \( \beta = 0 \) is rejected at 1% significance.

To determine the lag length in Equation (5) and (6), we test for joint significance of each group of lags with 5, 10, 15, 20, 25, and 30 minutes. With the criteria of minimum SBC, we find that 20-minute lag is optimum, and it is consistent with Darrat et al. (2007). We then test the null hypotheses to examine the Granger causality relationship between trading volume and volatility for both market opening hour and non-market opening hours.

Table II presents the empirical results for Granger causality relationship between trading volume and volatility for whole trading hours. In general, there is dual Granger causality between. However, trading volume positively affects volatility and volatility negatively affects trading

\[ ^{22} \text{For brevity, we do not report in detail. The results are available from the authors.} \]
volume. It is consistent with Darrat et al. (2007), which point out that investors trade to increase volatility but they are reluctant to close their positions afterwards.

Furthermore, according to overnight emotional change ($\Delta TVIX$), we apply the double-threshold model proposed by Tsay (1998) to divide the trading days into panic emotion if $\Delta TVIX \geq C_1$, optimistic emotion if $\Delta TVIX \leq C_2$, and normal emotion if $C_1 < \Delta TVIX < C_2$, where $C_1$ and $C_2$ are the two thresholds to estimate. The formal specification of the double-threshold model includes selecting the order $p$ for the three regimes. In this paper, since the relationships between trading volume and volatility for different overnight emotional change are investigated, we select the order $p = 0$. (i.e. the effect of overnight emotional change on the relationship between trading volume and volatility). Using Grid Search (Tsay, 1998), we obtain the optimum thresholds $C_1 = 0.056$ and $C_2 = -0.108$.

Under panic, normal and optimistic emotion, we explore the different relationships between volatility and trading volume, expected volume, and unexpected volume, which are decomposed by VAR, for market opening hour and non-market opening hours. The results are summarized in Table III and Table IV.

During market opening hours, the Granger causality between total trading volume and volatility as well as unexpected trading volume and volatility is consistent. Total trading volume and unexpected trading volume lead volatility, and volume uni-directionally Granger causes volatility for panic and optimistic emotion. In particular, volatility negatively leads total trading volume and unexpected trading volume only for normal emotion. Thus, it implies that for normal emotion investors’ trade to increase volatility but they are reluctant to close their positions afterwards.
On the other hand, it is evident that the relationship is asymmetric between expected trading volume and volatility for different emotions. For optimistic emotion, the relationship is unidirectional: expected trading volume does not lead volatility; however, volatility leads expected trading volume positively. Moreover, for panic and normal emotion, volatility leads expected trading volume negatively. It implies that investors are willing to trade in a volatile market only for optimistic emotion. In contrast with optimistic emotion, expected trading volume leads volatility negatively for panic and normal emotion. We conjecture that expected trading volume plays as volatility stabilizer for panic and normal emotion.

<<Insert Table IV About Here>>

During non-market opening hours, the lead-lag relationship is consistent in each situation with the exception of insignificance of unexpected trading volatility versus volume for optimistic emotion. The null hypothesis that volatility does not lead volume is not rejected at 1% significance. Furthermore, the relationship is positive for unexpected trading volume on volatility. Thus, it is evident that market reacts to overnight emotion during market opening hour, and it returns to normal lead-lag relationship: trading volume makes volatility, but volatility lowers trading volume. Compared with non-market opening hours, market opening hour does digest overnight information, especially for panic and optimistic emotion.

In general, we find that the relationship between total (expected, unexpected) trading volume is not always positive. From the perspective on causality, volatility lowers trading volume for whole trading hours. During opening hour, total (unexpected) trading volume makes volatility. For panic and optimistic emotion, volatility does not make total trading volume. It is not consistent with Mixture of Distribution Hypothesis (Clark, 1973), which proposes that trading volume and volatility is positively correlated. We conjecture that market may behave differently
for different time (market opening hours and non-market opening hours) and different (panic, normal and optimistic) market emotions.

During market opening hours, expected trading volume stabilizes volatility. On the other hand, unexpected trading volume leads volatility positively for panic and normal emotion. In addition to source of volatility, it implies more information content for unexpected trading volume (Lee and Rui, 2002; Speight et al., 2000).

After market opening hour, overnight emotion is digested, and volatility lowers total (expected, unexpected) trading volume, while (expected, unexpected) trading volume raises volatility (Darrat et al., 2007). The results are consistent with Sequential Information Arrival Hypothesis (Copeland, 1976) if $\Delta TVIX$ implies overnight information. However, since total trading volume and unexpected volume Granger cause volatility for normal emotion, Sequential Information Arrival Hypothesis is not totally sustained. We summarize the results of this paper as Table V.

IV. CONCLUSIONS

In this paper, we explore the relationship between volatility and trading volume in the panic and non-panic situations in the Taiwan market during the financial tsunami. In order to distinguish panic periods from non-panic ones, we apply the changes of Taiwan Volatility Index (TVIX) as the criteria. Besides, we apply Vector Autoregression (VAR) to decompose total volume into expected volume and unexpected volume to explore possible different relationship between the three volumes and emotional changes. It offers us a unique chance to better understand the market reaction for ‘fear’.

The study period covers three years (January 2nd, 2007 to December 31st, 2009), including important events during the financial tsunami. We find that there is bi-directional Granger causality between total trading volume and volatility: trading volume positively affects volatility,
and volatility negatively effects trading volume, and it is consistent with Darrat et al. (2007). However, we find the different relationships between volatility and total trading volume, expected trading volume, and unexpected trading volume under panic, normal and optimistic emotion. The relationship is asymmetric between expected trading volume and volatility for different emotions. For optimistic emotion, the relationship is uni-directional: expected trading volume does not lead volatility; however, volatility leads expected trading volume positively. Moreover, for panic and normal emotion, volatility leads expected trading volume negatively. In contrast with optimistic emotion, expected trading volume leads volatility negatively for panic and normal emotion. We conjecture that expected trading volume plays as volatility stabilizer for panic and normal emotion.

During non-market opening hours, the lead-lag relationship is consistent and it is shown that market reacts to overnight emotion during market opening hour, and it returns to normal lead-lag relationship: trading volume makes volatility, but volatility lowers trading volume. Compared with non-market opening hours, market opening hour does digest overnight information, especially for panic and optimistic emotion.

We find that the relationship between total (expected, unexpected) trading volume is not always positive. From the perspective on causality, volatility lowers trading volume for whole trading hours. During opening hour, total (unexpected) trading volume makes volatility. For panic and optimistic emotion, volatility does not raise total trading volume. It is not consistent with Mixture of Distribution Hypothesis (Clark, 1973), which proposes that trading volume and volatility is positively correlated, and it may be because of different market behaviors for different trading time and different market emotions.
During market opening hours, expected trading volume stabilizes volatility. On the other hand, unexpected trading volume leads volatility positively for panic and normal emotion. In addition to source of volatility, it implies more information content for unexpected trading volume (Lee and Rui, 2002; Speight et al., 2000).

After market opening hour, overnight emotion is digested, and volatility lowers total (expected, unexpected) trading volume, while (expected, unexpected) trading volume raises volatility (Darrat et al., 2007). The results are consistent with Sequential Information Arrival Hypothesis (Copeland, 1976) if the changes of TVIX imply overnight information. However, since total trading volume and unexpected volume Granger cause volatility for normal emotion, Sequential Information Arrival Hypothesis is not totally sustained.

References


### TABLE I

<table>
<thead>
<tr>
<th></th>
<th>Without intercept and trend</th>
<th>With Intercept only</th>
<th>With intercept and trend</th>
</tr>
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<tbody>
<tr>
<td><strong>Spot volume</strong></td>
<td>-209.949*</td>
<td>-307.723*</td>
<td>-308.462*</td>
</tr>
<tr>
<td><strong>Futures volume</strong></td>
<td>-447.130*</td>
<td>-447.129*</td>
<td>-447.135*</td>
</tr>
<tr>
<td><strong>Price return</strong></td>
<td>-404.891*</td>
<td>-404.890*</td>
<td>-404.890*</td>
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<tr>
<td><strong>Return volatility</strong></td>
<td>-295.621*</td>
<td>-296.212*</td>
<td>-296.220*</td>
</tr>
</tbody>
</table>

Note: 1. * implies significance at the 1% level.

2. Augmented Dickey-Fuller (ADF) statistic is obtained by

\[
\Delta y_t = \beta y_{t-1} + \sum_{t=1}^{p} c_t \Delta y_{t-1} + e_t
\]

(without intercept and trend),

\[
\Delta y_t = \alpha + \beta y_{t-1} + \sum_{t=1}^{p} c_t \Delta y_{t-1} + e_t
\]

(without intercept only),

\[
\Delta y_t = \alpha + \beta y_{t-1} + \sum_{t=1}^{p} c_t \Delta y_{t-1} + bt + e_t
\]

(with intercept and trend) where \( \Delta \) is the difference operator, \( \alpha, \beta, \) and \( c_t \) are coefficients to be estimated, \( y \) is the variable whose time series properties are examined and \( e \) is the white noise error term.

3. The lags of the dependent variable used to obtain white-noise residuals are determined using Akaike Information Criterion (AIC).

4. The null and the alternative hypotheses are respectively \( \beta = 0 \) (series is non-stationary) and \( \beta < 0 \) (series is stationary).
### TABLE II

Granger causality relationship between trading volume and volatility for whole trading hours

<table>
<thead>
<tr>
<th>Total trading volume versus volatility</th>
<th>F-value</th>
<th>Sign of sum of causal coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_0^1: \sum_{k=1}^{L} b_k = 0 )  [\text{(Volume does not lead volatility)}]</td>
<td>1346.9*</td>
<td>Positive</td>
</tr>
<tr>
<td>( H_0^2: \sum_{k=1}^{L} d_k = 0 )  [\text{(Volatility does not lead volume)}]</td>
<td>60.737*</td>
<td>Negative</td>
</tr>
</tbody>
</table>

Note: 1. * implies significance at the 1% level, and critical F-value is adjusted by Connolly (1989) to overcome Lindley’s paradox.

2. For brevity, we do not report on significance of each causal coefficient in detail. The results are available from the authors. Positive denotes that sign of sum of causal coefficients is positively significant at 1% level, and negative denotes that sign of sum of causal coefficients is negatively significant at 1% level. t-value is also adjusted by Connolly (1989) to overcome Lindley’s paradox.
### TABLE III
Granger causality relationship between trading volume and volatility for market opening hour

#### Panel A: Total trading volume versus volatility

<table>
<thead>
<tr>
<th>Panic emotion</th>
<th>Normal emotion</th>
<th>Optimistic emotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-value</td>
<td>Sign of sum of causal coefficients</td>
<td>F-value</td>
</tr>
<tr>
<td>$H_0^1: \sum_{k=1}^{L} b_k = 0$ (Volume does not lead volatility)</td>
<td>54.099* Positive</td>
<td>189.83* Positive</td>
</tr>
<tr>
<td>$H_0^2: \sum_{k=1}^{L} d_k = 0$ (Volatility does not lead volume)</td>
<td>7.5012 Insignificant</td>
<td>24.973* Negative</td>
</tr>
</tbody>
</table>

#### Panel B: Expected trading volume versus volatility

<table>
<thead>
<tr>
<th>Panic emotion</th>
<th>Normal emotion</th>
<th>Optimistic emotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-value</td>
<td>Sign of sum of causal coefficients</td>
<td>F-value</td>
</tr>
<tr>
<td>$H_0^1: \sum_{k=1}^{L} b_k = 0$ (Volume does not lead volatility)</td>
<td>9.1192* Negative</td>
<td>43.912* Negative</td>
</tr>
<tr>
<td>$H_0^2: \sum_{k=1}^{L} d_k = 0$ (Volatility does not lead volume)</td>
<td>35.395* Negative</td>
<td>128.62* Negative</td>
</tr>
</tbody>
</table>

#### Panel C: Unexpected trading volume versus volatility

<table>
<thead>
<tr>
<th>Panic emotion</th>
<th>Normal emotion</th>
<th>Optimistic emotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-value</td>
<td>Sign of sum of causal coefficients</td>
<td>F-value</td>
</tr>
<tr>
<td>$H_0^1: \sum_{k=1}^{L} b_k = 0$ (Volume does not lead volatility)</td>
<td>54.615* Positive</td>
<td>189.81* Positive</td>
</tr>
<tr>
<td>$H_0^2: \sum_{k=1}^{L} d_k = 0$ (Volatility does not lead volume)</td>
<td>7.4549 Insignificant</td>
<td>25.592* Negative</td>
</tr>
</tbody>
</table>
Note: 1. To overlap the trading hours for spot and futures markets, we define the time interval 9:00 to 10:00 as the market opening hour, the time interval 10:00 to 13:30 as the non-market opening hour. Panic, normal, and optimistic emotion are defined as $\Delta TVIX_t \geq 0.056$, $-0.108 < \Delta TVIX_t < 0.056$, and $\Delta TVIX_t < -0.108$ respectively. The thresholds -0.108 and 0.056 are estimated according to Tsay (1998).

2. * implies significance at the 1% level, and critical F-value is adjusted by Connolly (1989) to overcome Lindley’s paradox.

3. For brevity, we do not report on significance of each causal coefficient in detail. The results are available from the authors. Positive denotes that sign of sum of causal coefficients is positively significant at 1% level, and negative denotes that sign of sum of causal coefficients is negatively significant at 1% level. t-value is also adjusted by Connolly (1989) to overcome Lindley’s paradox.
**TABLE IV**

Granger causality relationship between trading volume and volatility for non-market opening hour

<table>
<thead>
<tr>
<th>Panel A: Total trading volume versus volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$H_0^1: \sum_{k=1}^{L} b_k = 0$ (Volume does not lead volatility)</td>
</tr>
<tr>
<td>$H_0^2: \sum_{k=1}^{L} d_k = 0$ (Volatility does not lead volume)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Expected trading volume versus volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$H_0^1: \sum_{k=1}^{L} b_k = 0$ (Volume does not lead volatility)</td>
</tr>
<tr>
<td>$H_0^2: \sum_{k=1}^{L} d_k = 0$ (Volatility does not lead volume)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Unexpected trading volume versus volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$H_0^1: \sum_{k=1}^{L} b_k = 0$ (Volume does not lead volatility)</td>
</tr>
<tr>
<td>$H_0^2: \sum_{k=1}^{L} d_k = 0$ (Volatility does not lead volume)</td>
</tr>
</tbody>
</table>
Note: 1. To overlap the trading hours for spot and futures markets, we define the time interval 9:00 to 10:00 as the market opening hour, the time interval 10:00 to 13:30 as the non-market opening hour. Panic, normal, and optimistic emotion are defined as 
\[ \Delta TVIX_i \geq 0.056, -0.108 < \Delta TVIX_i < 0.056, \text{ and } \Delta TVIX_i < -0.108 \] respectively. The thresholds -0.108 and 0.056 are estimated according to Tsay (1998).

2. * implies significance at the 1% level, and critical F-value is adjusted by Connolly (1989) to overcome Lindley’s paradox.

3. For brevity, we do not report on significance of each causal coefficient in detail. The results are available from the authors. Positive denotes that sign of sum of causal coefficients is positively significant at 1% level, and negative denotes that sign of sum of causal coefficients is negatively significant at 1% level. t-value is also adjusted by Connolly (1989) to overcome Lindley’s paradox.
TABLE V
Summary of Granger causality relationship between volume and volatility

<table>
<thead>
<tr>
<th>Market opening hour</th>
<th>Non-market opening hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panic</td>
<td>Normal</td>
</tr>
<tr>
<td>Total trading</td>
<td>Total trading</td>
</tr>
<tr>
<td>volume</td>
<td>volume ↔</td>
</tr>
<tr>
<td>→ Volatility</td>
<td>Volatility</td>
</tr>
<tr>
<td>Expected</td>
<td>Expected</td>
</tr>
<tr>
<td>trading</td>
<td>trading</td>
</tr>
<tr>
<td>volume ↔</td>
<td>volume ↔</td>
</tr>
<tr>
<td>Volatility</td>
<td>Volatility</td>
</tr>
<tr>
<td>Unexpected</td>
<td>Unexpected</td>
</tr>
<tr>
<td>trading</td>
<td>trading</td>
</tr>
<tr>
<td>volume →</td>
<td>volume ↔</td>
</tr>
<tr>
<td>Volatility</td>
<td>Volatility</td>
</tr>
</tbody>
</table>

Note: → and ← denote uni-directional Granger causality, and ↔ denotes bi-directional Granger causality.
Using the NPV and IRR Functions as Capital Budgeting Techniques
With Microsoft Excel

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Abstract

Microsoft Excel has two functions that can be extremely valuable in capital budgeting. One is the NPV function, the other is the IRR function. The NPV function, which Excel refers to as the Net Present Value function, computes the present value of a series of periodic cash flows that are not necessarily the same amount each period. The IRR function computes the internal rate of return of an investment project.

I. INTRODUCTION

Present Value of Periodic, but Unequal, Cash Flows

The NPV function is similar to Excel’s Present Value (i.e., PV) function, except that (1) the cash flows do not have to be the same amount each period, (2) the cash flows must occur at the end of each period, and (3) the function returns a positive value instead of a negative one. Whereas the PV function assumes a constant periodic cash flow, the NPV function computes the present value of cash flows that may differ from period to period. Since the NPV function only computes the present value of periodic cash flows, it does not compute net present value as defined in accounting and finance literature. Most authors define net present value as the present value of the future cash flows less the cost of the initial investment. For example, if a business purchased a new machine at the cost of $150,000 and the machine was estimated to provide the present value of net cash flows from future operations in the amount of $162,991 over a five-year period, the net present value of the investment would be computed as the net cash flows ($162,991) – cost of the investment ($150,000), which equals $12,991.

The NPV function’s syntax appears below:

\[ \text{NPV}(\text{Rate}, \text{Range of Values or Value}_1, \text{Value}_2, \ldots, \text{Value}_n) \]

where:
Rate = Discount rate for each period.

Range of Values = Represents a range of cells that contains the series of cash flow values, with the first cell in the range representing the cash flow for the first period and the last cell representing the cash flow for the last period. There is no practical limit on the number of cash flow values that you may include in the range.

Value1, Value2, ..., ValueN = Represents a list of up to 254 individual cash flows. NPV uses the order of value1, value2, ..., valueN to interpret the order of cash flows, with the first value representing the cash flow for the first period and the last value representing the cash flow for the last period. Be sure to enter the cash flow values in the correct sequence. In entering the individual cash flow values, you may enter either the values themselves or the cell addresses which contain the values.

The net present value (NPV) method is often used by a company to measure whether a proposed business investment will provide an adequate rate of return. For example, if the James Walter Manufacturing Corporation is considering an investment in new machinery costing $150,000, the company can forecast the future cash flows from the use of this new machinery and then use the NPV function to compute the present value of those cash flows discounted at the company’s cost of capital or at the interest rate required to finance the proposed investment. Regardless of whether the company uses its cost of capital or the required interest rate (i.e., discount) to finance the proposed investment rate, this rate represents the company’s minimum required rate of return.

To compute the net present value of the proposed investment, subtract the cost of the proposed investment from the present value of the future cash flows. Using this method, the company can
determine whether the investment exceeds, meets, or falls short of the company's minimum required rate of return. If the present value of the cash flows is greater than the cost of the proposed investment (NPV returns a value > 0), the proposed investment's expected rate of return exceeds the company's minimum required rate of return. If it is equal to the cost of the proposed investment (NPV returns a value of zero), the proposed investment's expected rate of return equals the minimum required rate of return. If it is less than the cost of the proposed investment (NPV returns a value < 0), the proposed investment's expected rate of return falls short of the minimum required rate of return. If a company’s resources and borrowing capacity are adequate and there are no alternative investments, the rule of thumb is simple: If a proposed investment’s NPV is greater than 0, make the investment. Otherwise, do not make the investment.

In the workbook file NewMach, there is a NPV worksheet. The NPV worksheet provides for a template similar to the one shown in Figure 1. In the template, cell E5 contains the company's minimum rate of return of 16.5%, cells C10 through C14 contain 5 years of estimated net cash flows provided by James Walter Manufacturing Corporation's investment in new machinery, cell D14 contains the estimated salvage value of the machinery at the end of 5 years, and cells E10 through E14 contain total cash flows for the five years.
The following NPV function, when entered in cell E19, will compute the present value of the annual cash flows discounted at the company’s minimum rate of return of 16.5%.

=NPV(E5, E10:E14)

Use the Function Arguments dialog box, pictured in Figure 2 to enter the NPV function in cell E19. In entering the cash flows values in the value argument(s), you can enter the range E10 through E14 as E10:E14 in the Value1 box; or you can enter the following in the value argument boxes:
Figure 2: Entering the Net Present Value of a Series of Periodic, but Unequal Cash Flows with the NPV Function

You enter a value in an argument box by clicking on the box and then either clicking on the cell address in the worksheet or entering the cell address at the keyboard. Similarly, in entering the range E10 through E14 in the Value1 box, click on the box and then either select the range E10 through E14 with the mouse or enter the range E10:E14 at the keyboard. Click on the OK button to enter the function in cell F17.

Complete the worksheet as follows:
1. Enter 150000, representing the cost of the proposed investment in new machinery, in cell E20.

2. Compute the net present value of the investment by entering the following formula in cell E22:

   =E19 - E20

3. Format cells E19 and E22 as currency ($) and cell E20 as comma (,). Click on the Decrease Decimal button in the Number group of the Home tab’s Ribbon as necessary in order to eliminate all decimal places for the three cells (i.e., E19, E20, and E22).

4. Underline the value in cell E20 and double-accounting underline the value in cell E22.

When completed, your worksheet should look like the one shown in Figure 3. As you can see in cell E19, the present value of the estimated cash flows from the use of the new machinery over the 5-year period, discounted at an estimated interest rate of 16.5 percent, is $162,991. When the $150,000 cost of the new machinery is deducted from the present value of the cash flows, the result is a net present value of $12,991 from the proposed investment. Since the net present value is positive (i.e., > 0), you can conclude that the expected rate of return on the proposed investment exceeds the company’s minimum rate of return of 16.5%. However, you don’t know by how much it exceeds the minimum rate of return.
Figure 3: Net Present Value of a Proposed Investment in New Machinery

<table>
<thead>
<tr>
<th>Estimated Net Cash Flows</th>
<th>Year</th>
<th>Cash Flow from Operations</th>
<th>Estimated Salvage Value</th>
<th>Total Cash Flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$43,500</td>
<td>$43,500</td>
<td>$43,500</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>46,250</td>
<td>46,250</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>49,750</td>
<td>49,750</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>51,500</td>
<td>51,500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>54,000</td>
<td>15,000</td>
<td>69,000</td>
<td></td>
</tr>
<tr>
<td>Total Non-Discounted Cash Flow</td>
<td></td>
<td></td>
<td>$260,000</td>
<td></td>
</tr>
</tbody>
</table>

| Present Value of Annual Cash Flows | $102,991 |
| Less: Cost of Investment | $150,000 |

Net Present Value of Investment | $12,991 |

INTERNAL RATE OF RETURN (IRR)

Consider the same forecasted cash flows from the investment in new machinery that was used for the NPV example in the previous section. The IRR worksheet in Figure 4 provides for a template similar to the one shown in Figures 1 and 3. In the template, cells C7 through C12 represent the estimated cash outflows or payments from the investment in new machinery; D7 through D12 represent estimated cash inflows from the investment; E12 represents the sale or salvage value of the machinery at the end of 5 years; and F7 through F12 represent estimated net cash inflows or outflows. Year 0 represents the initial cost of the investment. Any subsequent payments associated with the investment would be entered as cash outflows in the years in which the payments are made.
The following IRR function, when entered in cell F17, will compute the internal rate of return on the proposed investment in new machinery.

\[=\text{IRR}(F7:F12)\]

As noted previously, the guess argument is optional and is omitted in the above IRR function. Although you can enter the function at the keyboard, use the Function Arguments dialog box to enter the IRR function in cell F17, as shown in Figure 5. In entering the range F7 through F12 in the Values argument box, click on the box and then either select the range F7 through F12 with the mouse or enter the range F7:F12 at the keyboard. Click on the OK button to enter the function in cell F17.
Complete the worksheet by formatting cell F17 as follows:

- If necessary, change the number format to percent.
- Increase the number of decimal places to 3.
- Double-accounting underline the value in the cell.

When completed, your worksheet should look like the one shown in Figure 6. As you can see in cell F17, the IRR function shows the internal rate of return on the proposed investment in new machinery to be 19.922%.

If this expected rate of return is greater than the company’s cost of capital, then the proposed investment is considered economically viable. If alternative investments are being considered and if the risks associated with the investments are approximately equal, the rule of thumb is simple: To pick the best investment from a group of investments containing similar risks, select the one with the highest estimated internal rate of return, as long as the rate of return exceeds the company’s cost of capital.
II. CONCLUSION

Using Microsoft Excel’s NPV function enables the user to avoid common arithmetic errors as compared with computing it manually. Using the IRR function is even better. Why? Computing the estimated internal rate of return manually could take days. Instead, with the use of Microsoft Excel, you can compute the internal rate of return in a split second. More accurate and faster computing is why the NPV and IRR functions can be very helpful to both academicians and practitioners.
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