International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2017, 7(4), 300-315.

How Does Volatility of Characteristics-sorted Portfolios Respond to Macroeconomic Volatility?

Ahmed Al Samman[1]*, Mahmoud Moustafa Otaify[2,3]

[1]Department of Economics, Faculty of Economics and Political Science, Cairo University, Egypt, [2]Department of Finance, College of Business & Economics, Misr University for Science & Technology, Egypt, [3]Faculty of Economics & Political Science, Cairo University, Egypt. *Email: Elsamman@feps.edu.eg

ABSTRACT

This paper investigates how volatility of characteristics-sorted portfolios respond to macroeconomic volatility based on Egyptian data covering the period July 2002-June 2015. The paper uses three characteristics, namely size, book-to-market ratio and financial leverage to sort the most active stocks into corresponding characteristics mimicking portfolios. We examine how volatility of single characteristic mimicking portfolios as well as double characteristics mimicking portfolios respond to volatility in macroeconomic variables. The results indicate that the money supply volatility is the dominant source of volatility for the characteristics-sorted portfolios, followed by the inflation volatility. Both investors and policy makers should consider the volatility of money more than the interest rate channel in rebalancing their portfolios and formulating policies. Arguably, the low-frequency volatility of many portfolios tend to decrease during periods of global financial crisis and political uncertainty post the Egyptian revolution in 2011.

Keywords: Characteristics-sorted Portfolios, Macroeconomic Volatility, Spline-GARCH, Egyptian Exchange

JEL Classifications: G110, G120, G140

1. INTRODUCTION

Intuitively, corporate cash flows correlated considerably with the health of economy which translated directly into corporate stock prices. Therefore, both predicted and unpredicted changes in macroeconomic variables are expected to associate with movements in stock prices. Theoretical literature explores two channels through which the macroeconomic effects transmit to equity markets. Firstly, dividend discount model (DDM) indicates that stock price is a function of expected future cash flows and discount (required return) rate. The level of corporate cash flows depends on valuable investment opportunities which related strongly with gross domestic product (GDP) growth rate while inflation rate affect nominal cash flows and nominal interest rates (Zhang et al., 2009). Secondly, asset pricing theories attribute variations in the expected returns to systematic risks. Starting with the arbitrage pricing model developed by Ross (1976) which is the first model tried to explain cross-sectional variation in stock returns as a function of the macroeconomic variables. Most importantly, modern portfolio theory assumes that given the ability of investors to diversify their portfolios, they should be only awarded with extra long-term return against systematic economic risks, thus no additional return should be required for diversifiable risks (Chen et al., 1986). Moreover, It is well documented that time-variation of expected returns are attributed to the business conditions (Fama and French, 1989). For example, investors are more (less) likely to hold risk assets in periods of economic booms (recessions) and hence the expected returns tend to be low (high) (Kang et al., 2011). On the other hand, the underestimation of macroeconomic volatility[1] is considered as a main cause of the global financial and economic crisis (Cowen, 2009).

As financial markets promote economic growth through capital accumulation and allocation, the volatility in such markets has adverse effects. Volatility of stock return is widely considered as a measure of risk. Therefore, market participants, regulators,

1 The study will use interchangeably the terms of macroeconomic volatility, risk and uncertainty.

academicians and even media are interested in monitoring the level of stock market volatility in the home country. Moreover, volatility is a priced factor in the asset pricing models (e.g., French et al.,1987; Connor, 1995). Specifically, high volatility is responsible for increasing cost of capital (Choe et al., 1993), depressing market liquidity (Engle, 1993) and even current consumption (Raunig and Scharler, 2011) and investment (Hu, 1995). The importance of volatility for investment community encourages several researchers to study causes of stock market volatility. Actually, literature contains different explanations for stock market volatility including company fundamentals such as the impact of dividend policy (e.g., West, 1988; Ramadan, 2013), the impact of leverage (Christie, 1982), role of macroeconomic variables (e.g., Schwert, 1989; Morelli, 2002; Engle et al., 2013). Moreover, advocates of behavioral finance attribute changes in volatility to investor sentiment (e.g., Olsen, 1998; Verma and Verma, 2007).

In investment community, portfolio managers compete in designing strategies able to derive above the risk-adjusted returns. Many practitioners use fundamental characteristics such as firm size, book-to-market (BM) ratio and others to construct stock portfolios. Success of such strategies attracts the academic community to document and explain such evidence which contradicts with the efficient market hypothesis. Banz (1981) investigates the relation between the firm size and the return on NYSE stocks. Interestingly, he finds that smaller firms experienced higher returns than larger firms. Moreover, Basu (1977) documents that forming a portfolio of stocks with low price-earnings (PE) ratio are more likely to earn higher risk-adjusted return than high PE ratio stocks. Roseberg et al. (1985) argue that abnormal returns could be derived when investors follow a "BM" strategy – buy high BM ratio stocks and sell low BM ratio stocks. Subsequent excessive studies has provided strong evidence of such strategies but the pioneer evidence in this regard is provided by Fama and French (1993) when they has been documented the ability of size premium (the difference between returns on small and large cap stocks, SMB) and value premium (the difference between returns on high and low book to market ratio stocks; HML) in addition to the market risk premium to explain cross-sectional variation of stock returns. Their model is known as three factors Fama-French (3FF) model. Excessive number of subsequent researches have examined this model and others scholars augment other variables to the 3FF model. Carhart (1997) adds the price momentum as a fourth factor to the 3FF model while Chan and Faff (2005) investigate the role of share turnover (as a proxy of liquidity) in pricing Australian stocks. More recently, Mirza et al. (2013) use financial leverage mimicking portfolios to derive financial leverage premium and document its role in explaining cross-sectional expected returns. Subsequently, a wide empirical investigation has been implemented by several authors to validate the systematic risk factors related to the market, size, value, momentum and liquidity in both developed and emerging stock markets for explaining the cross-sectional expected returns (e.g., Cakici et al., 2013; Murtazashvilia and Vozlyublennaiab, 2013; Shaker and Elgiziry, 2014).

2. LITERATURE REVIEW

Despite of the superiority of the 3FF model in explaining cross-section return in many countries, it can be lost at some point of time if the factors (SMB, HML) are anomalies but if they are risk factors, the model keep its superiority than capital asset pricing model in pricing risky assets (Vassalou, 2000). Thus, it becomes more vital to examine whether the size and BM factors are associated with fundamental risk in the economy. In this regard, financial literature has several attempts to directly examine asymmetric response of characteristics mimicking portfolios to macroeconomic variables. Perez-Quiros and Timmermann (2000) use the two-state Markov switching model and find that both risk and expected returns on small stocks are the most sensitive to changes in economic variables in recession state as compared to the risk and return on big stocks. Vassalou (2000) points out that the SMB and HML contain information regarding two fundametal sources of risk in the economy; the current default premium and news about future GDP growth. Zhang et al. (2009) find that value and small stocks earn greater returns during periods of higher GDP growth as well as in periods of low interest rates. Moreover, the unexpected inflation has opposite impacts on risk premiums; it affects negatively the size premium and positively affects the value premium. The term spread is positively related to the returns premiums. Using the two-state Markov switching model Gulen et al. (2011) document that, in the period of high conditional volatility, the expected return of value portfolio is more responsive to economic conditions than that of growth portfolio. Cenesizoglu (2011) analyze how daily and monthly returns on value/growth and large/small stocks react to news about macroeconomic variables. The author finds that large and growth stocks are more sensitive to the employment news than small and value stocks in expansion periods. Kang e al. (2011) examine the time-varying patterns in stock returns by investigating the effects of dividend yield, default spread, term spread and short-term interest in addition to the SML and HML variables on excess returns of the 25 size and BM sorted portfolios. They document that both dividend yields and short-interest rates negatively, significantly related to the cross-sectional expected returns which imply that using only market return, SML and HML variables could fail to capture the time-varying patterns of expected return. Kontonikas and Kostakis (2013) argue that portfolios constructed on the basis of fundamental characteristics are not only convenient to investigate the soundness of the monetary policy channels but also to investigate the existence of other channels. In particular, they expect that the balance sheet channel could play a role in explaining the response of value-sorted portfolios to monetary policy shocks while the bank lending channel is more suitable to interpret the response of size-sorted portfolios. Their findings reveal that value, small and past loser – sorted portfolios are more sensitive than growth, big and past winner – sorted portfolios to the unexpected US monetary policy shocks in the period 1967-2007. Some studies explain the asymmetry response of individual stocks to monetary shocks to the degree of financial constraints. For example, Ehrmann and Fratzscher (2004) argue that low financial leveraged firms have the largest effect of monetary policy maybe because they currently face financial constrains that prevent them to borrow more debt. Consistent with this argument, Basistha and Kurov (2008) document that financial constrained portfolios are more sensitive to the monetary shocks in tight credit conditions than the unconstrained firms and attribute their results to the credit channel of monetary policy transmission.

Other studies try to model volatility (risk) of the characteristic-sorted portfolios. Li et al. (2009) estimate volatility properties of value, growth and HML portfolios in the context of GARCH model and convey interesting results. Firstly, volatility of value portfolio is more (less) sensitive to recent (older) information than that of growth portfolio. Secondly, volatilities of both the value portfolio and the HML portfolio are indifferent for good or bad news but volatility of the growth portfolio increases after announcement of bad news. Finally, using GJR-GARCH (1,1)-M model, the authors document a positive, significant relation between the excess return of the value portfolio and the time-varying volatility while the excess return of the growth portfolio is negatively related to volatility, and therefore the expected return of the value premium (HML portfolio) is positively associated with its time-varying volatility. Thereby, the authors argue that return on the value portfolio is more sensitive to its volatility than the growth portfolio.

Very few studies have investigated the relationship between macroeconomic risk and volatility of stock portfolios constructed on the fundamental characteristics. Black (2006) examines the relationship between the conditional volatilities of real GDP and default risk premium and the conditional volatilities of the Fama and French three-factor model using US quarterly data during the period 1923-2002. She finds that volatility of value premium is more sensitive to the volatility of default premium than the volatility of size premium. Although volatility of market risk premium can predict volatility of GDP growth but the volatility of both value premium and size premium cannot. Results of Black's study imply the existence of significant and different relationships between volatility of the Fama–French factors and the macroeconomic volatility.

Our study contributes to the literature in three ways. Firstly, the question about the asymmetric response of volatilities in the characteristics-sorted portfolios to the macroeconomic volatility is still unaddressed (Cenesizoglu, 2011), thus the current paper seeks to fill this gap, at least on the level of Egyptian stock markets as an emerging market. Moreover, the paper does not construct only portfolios according to a single characteristic (as previous papers) but also use double-sorted portfolios so as to understand the interaction between the underlying characteristics (size, book-market ratio and financial leverage) and how the generated return series will react to the macroeconomic volatility. Thirdly, to our best of knowledge, the current paper is the first study that uses the spline-GARCH model to estimate the low-frequency volatility of stock returns using data from the Egyptian exchange and takes into the account the potential effects of global financial crisis and political instability (due to the Egyptian revolution in 2011).

The remaining parts of current paper is organized in four sections as follows. Section 3 presents data collection and variables selection. Section 4 explores methodology and empirical procedures used to test the relation between macroeconomic volatility and portfolio volatility. Section 5 shows the estimation results and discussion. Finally, section 6 highlights conclusion and recommendations.

3. DATA, VARIABLE CONSTRUCTION AND HYPOTHESIS DEVELOPMENT

3.1. Data

The paper uses daily prices of stocks listed on the Egyptian exchange over the period 3 July 2002-29 June 2015. The main source of daily trading data is Egypt Information Dissemination Company. Volatility analysis needs active stocks, thus the paper follows a criteria based on number of trading days to select the most active stocks. Typically, stocks which satisfy the 80% of total trading days, in each year, will be selected in the sample. To sort stocks in portfolios according to their fundamental characteristics; BM ratio and financial leverage, financial reports of the selected stocks are hand collected to record figures of book values and total assets from their balance sheet. Most macroeconomic variables are available on monthly frequency, thus monthly data on short-term interest rates and money supply collected from central bank of Egypt; the consumer price index (CPI) from CAMPAS[2]; total production index[3] from ministry of planning; the stock market index data from the Egyptian exchange.

3.2. Variable Construction and Hypothesis Development

Most previous studies adopt the DDM as a common theoretical background to select the macroeconomic variables that potentially affect the stock return volatility. Plausibly, whether the current stock prices are affected significantly by information regarding the expected dividends and the expected discount rate, it will be reasonable to assume that volatility of current stock price will be affected by the volatility of expected future dividends and future discount rate and by the covariance between them (Morelli, 2002). The cash flows are related to business conditions which can be represented by selected key macroeconomic variables including CPI, foreign exchange rate (FX), real growth of total production index, money supply (M2), short-term interest rates. Since the paper attempts to explain volatilities of different style portfolios, it is reasonable to test their sensitivity to the stock market volatility (proxied by volatility of the return on the Egyptian official stock market index; EGX30).

The impact of global financial crisis on the Egyptian exchange appear aggressively since mid-September 2008 when foreign investors liquidated their portfolios to cover their losses in their home countries which resulted in a drop in the EGX 30 index by 52% (EGX, 2008). At the end of September 2009, EGX 30 index exceeded the 7000 points which is considered as the highest record over the last 12 months (EGX, 2009). Thus, the current paper uses the period September 2008-August 2009 to investigate the effect of the financial crisis and their effect on the relation between the macroeconomic volatility and the stock return volatility. In this regard, this paper follows Chinzara (2011) and adds a dummy variable which takes 1 in the period of financial crisis (September 2008-August 2009) and zero otherwise.

2 CAMPAS refers to Central Agency for Public Mobilization and Statistics.

3 The Egyptian Ministry of Planning issued the Monthly Production Index which started from May 2002. This index comprises 60% of the entire economic activities; Manufacturing, Natural gas, Oil Products, Electricity, Construction, Transportation, Suez Canal and Tourism.

On the 25th of January 2011, Egyptians overthrew the president Mubark and consequently the Egyptian country witnessed political instability. On the subsequent trading days, the 26th and 27th of January, the EGX 30 index dropped sharply by 30% and 16% respectively. As a result of the security absence, banks are closed and trading on EGX is suspended for almost 2 months. To protect investors' rights, EGX adopts precautionary procedures to resume trading on the 23rd of March, 2011. Similarly, the paper uses another dummy variable to reflect the period of the political uncertainty post the Egyptian revolution which takes 1 during the period: 25 January 2011-21 July 2014 and zero otherwise.

3.3. Formation of Size and BM Ratio Sorted Portfolios

There is an extensive literature on the capability of characteristics - mimicking factors in capturing the cross-sectional variation in stock returns. The recent empirical study on Egyptian stock market indicated the importance of the market return, size effect and value effect; i.e., the Fama-French Three model and rejected the significance of both liquidity and momentum factors (Shaker and Elgiziry, 2014). However, to our best knowledge, financial leverage mimicking portfolios are not tested in the Egyptian stock market. On the other hand, financial leverage is strongly related to stock return volatility. Therefore, the current study uses the financial leverage in addition to the BM ratio and size to form the characteristics-sorted portfolios. Typically, size is measured as the market value of firm's equity (its market capitalization) at the end of June each year. BM ratio is the ratio of the book value of equity (proxied by total stockholders' equity) at the end of financial year to the market value of the equity at the end of June. Finally, the financial leverage is the ratio of total assets to total stockholders' equity. To avoid the look-ahead bias, following to previous studies (e.g., Fama and French, 1993), the paper uses the 6-months lagged value of BM ratio and financial leverage to ensure the availability of financial statements to the investors to the marketplace at the time of the portfolios construction. Prior to form portfolios, the underlying sample of stocks will be subjected to two procedures; arranging and classifying. The arranging procedure refers to ordering stocks descending according to a specific firm-characteristic. The classifying procedure indicates to grouping stocks into a single characteristic-sorted portfolio according to specific breakpoints. Following to the literature, we apply 50-50% breakpoints to sort stocks according to their size into big (top 50%) and small (bottom 50%) portfolios and apply the breakpoints (30-40-30) to sort the stocks according to their BM ratio into value (top 30%), core (middle 40%) and growth (bottom 30%) and finally, apply the 50-50% breakpoints to sort stocks according to their financial leverage into high (top 50%) and low (bottom 50%) financial leverage portfolios. These seven portfolios jointly construct 16 portfolios which called the double characteristics-sorted portfolios as shown on Table 1.

4. METHODOLOGY

4.1. Measuring Portfolio Return

The continuously compounded daily returns on each stock, $R_{i,n,t}$, in a portfolio are computed as:

$$R_{i,n,t} = ln\left(\frac{P_{i,n,t}}{P_{i,n-1,t}}\right)\times 100 \tag{1}$$

Where $P_{i,n,t}$ denotes the closing price of stock i on day n of month t. We use the equal weighted basis, to calculate the daily portfolio returns because it is more appropriate for examining returns on different portfolios in a separation of the size effects (Barnard and Bunting, 2015).

However, the literature provides a weak empirical evidence on the explanatory power of macroeconomic uncertainty for stock market volatility. Jones et al. (1998) attribute the low R^2 to misspecification of financial market volatility. In this regard, Engle and Rangel (2008) argue that decomposition of volatility into high frequency and low frequency volatilities could accurately model volatility. Engle and Rangel use spline-GARCH model to generate the low-frequency volatilities of 50 stock markets and then estimate them as a function of the macroeconomic volatility. Azad et al. (2011) also use the spline-GARCH model to extract the low-frequency volatility of Japanese yen interest rate swap and then estimate it as a function of macroeconomic volatility. Similarly, Liu et al. (2015) examine the impact of the macroeconomic volatility on the low-frequency volatility of gold futures markets in China. Therefore, we employ the spline-GARCH to estimate the low-frquency volatility of characteristics-sorted portfolios and explain it in realtion to the macroconomic volatility.

4.2. Estimating and Decomposing Aggregate Portfolio Return Volatility

To understand the notion of spline-GARCH model more better, it is preferable to review the standard GARCH (1,1) model of Bollerslev (1986) which consists of two equations; mean equation and conditional variance equation:

$$r_t - E_{t-1}r_t = \sqrt{h_t}\,\mu_t, \tag{2}$$

$$\mathrm{h}_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta \mathrm{h}_{t-1}, \tag{3}$$

$$\varepsilon_t | I_{t-1} \sim N(0,1)$$

Where r_t is the stock return at time t, ε_t is the innovation term assumed to have zero mean and variance 1. The expectation E_{t-1} is conditional on information set I_{t-1} including historical past returns up to time $t-1$, h_t decribes the corresponding conditional variance of stock returns at time t. The coefficients α and β stand for the ARCH term and the GARCH term, respectively. GARCH model assumes that conditional volatility is mean-reverting to a constant level while the unconditional volatility is constant. GARCH model is able to capture volatility dynamics in short term but it does not account for more permanent and/or slow-moving behavior of volatility (Adrian and Rosenberg, 2008). However, time series analysis for the realized volatility of stock returns documents abnormal high or low volatility for a decade (Engle and Rangel, 2008). Therefore, to capture the low-frquency volatility of stock returns, we need a model that allows unconditional volatility to vary slowely over time. Engle and Lee (1999) introduce the component GARCH model bywhich volatility can be decomposed into two components. The first component characterizes the short-run conditional volatility related to the transitory effects of volatility. The second component describes the slower variations in volatility process which can be attributed to permanent effects of volatility. However, the slow-moving trend in volatility process

Table 1: Characteristics-sorted portfolios

Sorting characteristics	Size		BM ratio			Financial leverage	
	Big(B)	Small (S)	Value (V)	Core (C)	Growth (G)	High (H)	Low (L)
Panel A		Panel B		Panel C		Panel D	
Single characteristic-sorted portfolios		Size and BM ratio-sorted portfolios		Size and financial leverage-sorted portfolios		BM ratio and financial Leverage-sorted portfolios	
B	S	BV	SV	BH	SH	VH	VL
V C G		BC	SC	BL	SL	CH	CL
H	L	BG	SG			GH	GL

BM: Book-to-market

generated by the component GARCH model is mean-reverting to a constant level. Engle and Rangel (2008) relax this assumption and modify the GARCH model by approaching nonparametrically a trend using an exponential quadratic spline, which generates a smooth curve that is able to describe the low-frequency volatility component in the volatility process. Therefore, The spline-GARCH model of Engle and Rangel (2008) is able to decompose the daily stock return volatility into high- and low-frequency components as follow:

$$r_t - E_{t-1}r_t = \sqrt{h_t}\,\varepsilon_t, = \sqrt{g_t\tau_t}\,\varepsilon_t ; \varepsilon_t \mid I_{t-1} \sim N(0,1) \quad (4)$$

$$g_t = (1-\alpha-\beta)+\alpha\left(\frac{(r_t - E_{t-1}r_t)^2}{\tau_{t-1}}\right)+\beta g_{t-1}, \quad (5)$$

$$\tau_t = c\,exp\left(\omega_0 t+\sum_{i=1}^{k}\omega_i\left(\left(t-t_{i-1}\right)_+\right)^2\right), \quad (6)$$

Where I_{t-1} denotes an extended information set including the history of portfolio returns up to day t−1. The term g_t is the high-frequency component while τ_t is the low-frequency component. τ_t has a persistent (long-term) impact on h_t while g_t does not have (Azad et al., 2011). The former component can be attributed to short-term market skewness risk while the latter component is attributed to the long-term or macroeconomic risk (Adrian and Rosenberg, 2008). $\omega_0 t$ is a time trend in the low-frequency volatility, $\sum_{i=1}^{k}\omega_i\left(\left(t-t_{i-1}\right)_+\right)^2$ is a low-order quadratic spline. The coefficients ω_i measures the sharpness (i.e., the duration and strength) of each cycle described by the spline. Values of knots k, determine the number of cycles by dividing the sample (time horizon) into k equal parts (spaced intervals): $1 < t_1 < t_2 <...< t_k < t$. High value of implies that the number of cycles increases and duration of each cycle shortens. However, value of is unobservable and thus we follow Engle and Rangel (2008), to use the Bayesian information criteria (BIC) to choose the optimal number of knots k. A special feature of spline-GARCH model of Engle and Rangel (2008) is that the unconditional volatility coincides with the low-frequency volatility:

$$E[(r_t - E_{t-1}r_t)^2]=\tau_t\, E(g_t)=\tau_t \quad (7)$$

4.3. Low-frequency Portfolio Return Volatility and Macroeconomic Volatility

The generated series of time-varying low-frequency (unconditional) volatility are on daily basis while most macroeconomic variables are available on monthly frequency. Therefore, we need firstly to construct a monthly low-frequency volatilities from the daily low-frequency volatilities as follows:

$$Lowvol_{i,t} = \sqrt{\frac{1}{N}\sum_{d=1}^{N_{i,t}}\tau_{i,d,t}} \quad (8)$$

Where $Lowvol_{i,t}$ denotes low-frequency volatility of portfolio return i in month t. $N_{i,t}$ is the number of trading days in a month t for portfolio i. $\tau_{i,d,t}$ is the daily low-frequency volatility observed for portfolio i, at trading day d of month t. Secondly, we follow the previous studies (Schwert, 1989; Girardin and Joyeux, 2013; Engle et al., 2013) to estimate monthly macroeconomic volatility by fitting an AR (12) model with twelve monthly dummy variables (to allow for different monthly mean changes in the macroeconomic variables) to the first difference of the log of the selected macroeconomic variables (except nominal interest rates, NIR) and use the estimated squared residuals as proxies of the monthly volatilities. Finally, we can examine the role of macroeconomic volatility in explaining volatility of characteristics-sorted portfolios using the following empirical model:

$$Lowvol_{i,t}=c_{i,0}+\theta_{i,1}EGXvol_t+\theta_{i,2}CPIvol_t+\theta_{i,3}FXvol_t+\theta_{i,4}RPGvol_t+\theta_{i,5}M2vol_t+\theta_{i,6}NIRvol_t+\mu i,t \quad (9)$$

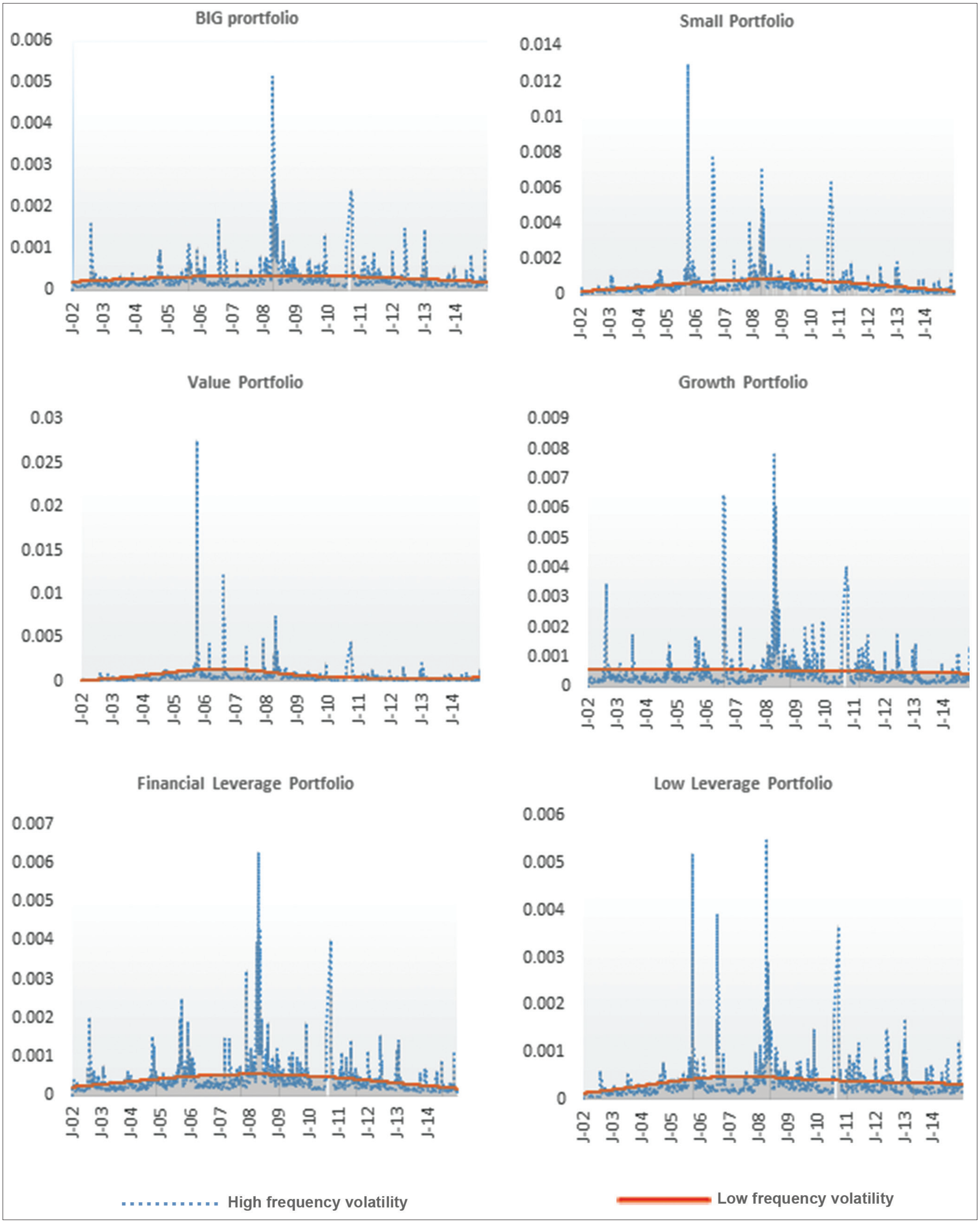
Where *EGXvol,* volatility of Egyptian formal index (EGX30); *CPIvol*, volatility of consumer price index; *FXvol*, foreign exchange volatility; *RPGvol*, volatility of real production growth; *M2vol*, money supply volatility; *NIRvol*, volatility of short-term interest rates, in month t. Regarding the potential effect of global financial crisis as well as the effect of political instability associated with the Egyptian revolution in 2011 and the subsequent events, Eq. (9) is augmented to include two dummy variables for both effects as follows:

$$Lowvol_{i,t}=c_{i,0}+\theta_{i,1}EGXvol_t+\theta_{i,2}CPIvol_t+\theta_{i,3}FXvol_t+\theta_{i,4}RPGvol_t+\theta_{i,5}M2vol_t+\theta_{i,6}NIRvol_t+\theta_{i,7}DUMcrisis_t+\theta_{i,8}DUMpol_t+\mu_{i,t} \quad (10)$$

Where $DUMcrisis_t$ is a dummy crisis reflecting effect of the global financial crisis, takes one in month during the crisis period and zero otherwise. $DUMpol_t$ is a dummy variable shows the effect of political uncertainty associated with the Egyptian revolution, takes one in month t during the precautionary period and zero otherwise.

Figure 1 depicts the estimated daily low-frequency volatility (using Eq. 6) and high-frequency volatility (using Eq. 5) components for selected single-characteristics sorted portfolios over the period from July 2002 to June 2015. The high-frequency component is related

Figure 1: Low and high frequency volatility series for selected single-sorted portfolios



to the short-run conditional volatility while the low-frequency component is related to the slow-moving trend that characterizes the unconditional volatility (Azad et al., 2011). It is evident that volatility components do not follow the mean-reverting pattern. The solid line refers to the low-frequency component while the dotted line refers to the high-frequency component.

Table 2: Descriptive statistics for macroeconomic variables

Measure	*REGX*	*GCPI*	*GFX*	*GRPI*	*GM2*	*NIR*
Mean	0.019608	0.007464	0.003114	−0.0014	0.010793	0.070577
Median	0.022788	0.006406	0.00063	−0.0056	0.010286	0.07
Maximum	0.311919	0.03875	0.148569	0.198653	0.371953	0.0946
Minimum	−0.40334	−0.0154	−0.12397	−0.21578	−0.3529	0.059
Standard deviation	0.094947	0.008803	0.019676	0.073187	0.042363	0.008477
Skewness	−0.47784	0.466327	1.63378	0.163254	−0.0759	0.442701
Kurtosis	5.136671	4.052322	33.65494	3.463712	70.49861	2.657952
Jarque-Bera	35.15485	12.68719	6098.415	2.063831	29234.88	5.780983
Probability	0.00000	0.00176	0.00000	0.35632	0.00000	0.05555
Observations	154	154	154	154	154	154

5. EMPIRICAL RESULTS AND DISCUSSION

5.1. Descriptive Statistics

Table 2 shows descriptive statistics for the growth of macroeconomic variables. Stock market return and money supply seem to have grown the fastest, followed by CPI. The total production index has grown negatively over the study period. Typically, stock market index is the most volatile as a financial variable while the real production growth is the most volatile macroeconomic variable, followed by money supply but interest rates is the least volatile variable. Both stock market return and money supply growth are negatively skewed (i.e., their distribution has a long left tail) while inflation, foreign exchange rate and real production growth are positively skewed (i.e., their distribution has a long right tail). The kurtosis ratio shows that the distribution of the real production growth is normal because its Kurtosis value around 3. This result is confirmed by the Jarque–Bera statistic for normal distribution which does not reject null hypothesis that the series is normally distributed. The Kurtosis value for nominal interest rate is less than 3 which means that its distribution is flat (platykurtic) relative to the normal. The Kurtosis ratio for other macroeconomic variables including stock market returns show that their distribution is peaked (leptokurtic) relative to the normal. Consistently, the null hypothesis of the Jarque-Bera test for normal distribution is rejected.

Table 3 presents average monthly return as well as standard deviations of characteristics-sorted portfolios in four panels; panel A for single characteristic-sorted portfolios, panels B, C, and D for size and BM ratio-, size and financial leverage-, and BM and financial leverage-sorted portfolios, respectively. For the full period (July 2002-June 2015), small (S), value (V), core (C), high (H) leverage portfolios have positive monthly returns while big (B), growth (G) and low (L) leverage portfolios have negative average returns. As expected, returns on S, V and H portfolios outperform returns on B, G and L portfolios. Similarly, the S, V and H portfolios are riskier than B, G and L portfolios. Moreover, the G (H) portfolio has the highest monthly negative (positive) returns as compared to other single characteristic-sorted portfolios. In terms of standard deviations, S portfolio has the highest value of standard deviation, 15.24% while B portfolio has the smallest value, 9.37%. With respect to the size-BM ratio-sorted portfolios, small-core (small-growth) portfolio has the highest positive (negative) monthly return. In panel C, the big-high leverage portfolio not only has the highest positive return but also has lower risk than both small-high and small-low portfolios. In panel D, value-high leverage (VH) has the highest level of both positive return (1.02%) and risk (16.3%) while the growth-low leverage (GL) has the highest negative return, −2.35% at standard deviation of 14.35%. Overall, in full period, both the small-core portfolio and value-high leverage portfolio have the highest positive monthly return, 1.12% and 1.02% respectively while the small-growth portfolio has the highest standard deviation of 19.13%.

During normal conditions period (July 2002-August 2008), S, V and H portfolios have both higher returns and risk than B, G and L portfolios. The high leverage (H) portfolio has the highest return as compared to other single characteristic-sorted portfolios. Small-core portfolio has the highest return of 3.95%, followed by the small-value portfolio, 2.25% in panel B. Although returns on the small-high leverage portfolio and the big-high leverage portfolio are very close, 2.81% and 2.75% respectively, the former is more volatile than the latter in terms of the standard deviations; 15.55 > 10.36% as shown in panel C. Similarly in panel D, returns to the value-high leverage portfolio and the core-high leverage portfolio are 3.82% and 3.87% respectively while their associated risks 19% and 14% respectively. These statistics imply that constructing portfolios based on different characteristics rather than based on single ones will provide investors with higher returns at different levels of risk. Collectively, stocks characterized as small-core-high leverage or characterized as small-value-high leverage are more likely to earn higher returns under normal market conditions.

During the global financial crisis period (September 2008-August 2009), it is evident that volatility level is high for all portfolios where standard deviations range from 16.2% to 29.7%. Despite small portfolio is the most volatile (with standard deviation, 23.7%) among the single characteristic-sorted portfolios, it is the only one which performs, on average, positively (with mean, 0.21%) during the crisis period. Statistics for panel B reveals that small-value, small-core and small-growth portfolios have positive returns and conversely the big-value, big-core and big-growth portfolios. The small-growth portfolio earned the highest average return, 0.48% and also associated with the highest level of risk (29.7%) while the big-value portfolio has the lowest volatility level (16.22%) in panel B. In panel C, the small-low leverage portfolio only is witnessed with positive returns, 0.61%, at high risk, 23.5%. In panel D, the value-low leverage portfolio only has positive returns, 0.21%. Different performance of portfolios during the crisis period is consistent with the argument of Elton et al. (2014) who suppose that combing stocks with different characteristic may offer diversification in distress period**.** According

Table 3: Mean and SD of portfolios during different periods

Portfolios*	Mean±SD			
	Full period (%)	Normal period (%)	Crisis period (%)	Political uncertainty period (%)
Panel A				
B_r	−0.17±9.37	1.33±8.24	−2.09±17.64	−0.61±9.29
S_r	0.23±15.24	2.57±15.07	0.21±23.74	−1.15±13.21
V_r	0.24±13.17	1.89±14.07	−0.38±20.08	−0.86±11.30
C_r	0.32±10.92	2.48±9.74	−1.56±18.63	−0.88±10.53
G_r	−0.87±12.46	0.83±10.55	−1.00±23.57	−0.94±11.66
H_r	0.38±12.35	2.82±11.73	−1.59±22.15	−1.06±11.07
L_r	−0.34±11.21	1.03±10.01	−0.61±18.76	−0.70±11.05
Panel B				
BV_r	0.02±11.99	1.12±13.63	−0.71±16.22	−0.44±10.33
BC_r	−0.13±9.76	1.73±8.40	−2.74±19.53	−0.61±8.55
BG_r	−0.58±10.18	0.84±10.15	−3.14±16.37	−0.68±9.73
SV_r	0.27±16.44	2.25±17.56	0.12±25.16	−1.34±13.19
SC_r	1.12±14.46	3.95±15.02	0.35±18.35	−1.20±12.89
SG_r	−1.06±19.13	1.52±19.74	0.48±29.74	−0.89±14.67
Panel C				
BH_r	0.38±10.87	2.75±10.36	−3.27±20.05	−0.71±9.77
BL_r	−0.52±9.09	0.41±7.96	−1.55±16.65	−0.55±9.13
SH_r	0.28±15.57	2.81±15.55	−0.21±24.30	−1.53±13.69
SL_r	0.17±16.00	2.33±16.53	0.61±23.46	−0.86±13.05
Panel D				
VH_r	1.02±16.30	3.82±19.01	−1.58±23.18	−1.05±11.40
VL_r	0.10±12.84	1.36±13.59	0.21±18.85	−0.64±11.36
CH_r	0.75±13.76	3.87±14.40	−1.37±21.30	−1.59±10.95
CL_r	0.18±10.29	1.90±8.67	−1.66±16.68	−0.45±10.99
GH_r	−0.07±12.23	1.85±10.59	−1.58±23.73	−0.47±11.80
GL_r	−2.35±14.35	−1.31±12.65	−0.25±24.09	−1.53±12.21

*r denotes return and added to each name of the portfolios to indicate the portfolio return. SD: Standard deviation

to statistics, stocks characterized as small, value and low financial leverage are more likely to perform well in period of financial crisis.

During the period of political uncertainty (January 2011-July 2014), the risk level (in terms of standard deviations) ranges from 8.6% to 14.7% indicating that all portfolios experience less volatility as compared to their corresponding volatility level in the financial crisis period. More specifically, the small, the small-growth, the small-high and the growth-low portfolios experience greater volatilities in panels A, B, C and D respectively. Moreover, the negative monthly returns earned by all portfolios indicate that most investors are pessimistic and worry about the political instability which significantly, negatively affect the corporate future cash flows. On the other hand, this period coincides with the precautionary procedures adopted by the Egyptian exchange whereby the trading secession is shortened and imposing price limits to minimize the expected excessive volatility in the stock market. Thereafter, this drop in volatility levels for all portfolios reflect the efficiency of these procedures. In terms of return, the big portfolio, the big-value, the big-low leverage and the core-low leverage portfolios experience the smallest negative returns in panels A, B, C and D respectively. This indicates that stock characterized as big-value-low leverage are less sensitive to political events than other portfolios.

5.2. Estimation Results of the Spline-GARCH Model for the Portfolio Returns

Based on the daily returns for each portfolio, we estimate the spline-GARCH model of Engle and Rangel (2008) to generate the low-frequency volatility of each portfolio. Table 4 presents the estimation results of the spline-GARCH model for two types of portfolios; single characteristic and double characteristics. The paper tries up to 5 knot points and uses BIC criteria to select the optimal number of knots, k in the spline-GARCH model. Since this number, k, refers to the cyclical effects in the series, higher value of k indicates more frequent (business) cycles (Azad et al., 2011). Table 4 shows different portfolios have different numbers of knots according to the minimum BIC. All single characteristic-sorted portfolios (except value portfolio and low leverage portfolio) have only 1-knot point which reflects less cyclical effects in their series. The number of knots varies for the double characteristics-sorted portfolios where small-high leverage (SH), growth-high leverage (GH) and growth-low leverage (GL) portfolios have 5-knot points while small-value (SV), value-high leverage (VH) and value-low leverage (VL) portfolios have 4-knot points. As preliminary analysis, SH, GH, GL, SV, VH and VL portfolios may have stronger relationship with the macroeconomic volatility than other double characteristics-sorted portfolios. Alternatively, the dissimilarity among portfolios in number of knots can be due to the variations in the volatility patterns of the portfolios and their differential responses to the business cycle risks over the period under estimation (Azad et al., 2011).

Alpha (α) and beta (β) coefficients represent the ARCH and GARCH effects, respectively in the spline-GARCH model. Both are positive and significant at 1% level for all portfolios. The presence of ARCH effect indicates that previous volatility has significant effect on current volatility while the presence of

Table 4: Estimation results of spline-GARCH for characteristics-sorted portfolios

Panel A	Single characteristic-sorted portfolios							
Portfolio	Knots[a]	Obs	Obs/Knot[b]	Alpha[c]	Beta[d]	Alpha+beta	Log likelihood	BIC
B_r	1	3146	3146	0.15096	0.802985	0.953945	8929.8	−5.659
S_r	1	3146	3146	0.161789	0.782739	0.944528	7913.0	−5.0126
V_r	2	3146	1573	0.174966	0.779159	0.954125	8066.5	−5.1076
C_r	1	3146	3146	0.151456	0.775908	0.927364	8615.3	−5.4591
G_r	1	3146	3146	0.177508	0.783162	0.96067	8276.0	−5.2459
H_r	1	3146	3146	0.159487	0.779148	0.938635	8311.2	−5.2658
L_r	2	3146	1573	0.146059	0.811296	0.957355	8666.8	−5.4893
Panel B	**Size and BM ratio-sorted portfolios**							
BV_r	2	3146	1573	0.142088	0.776237	0.918325	7844.3	−4.9663
BC_r	2	3146	1573	0.134593	0.768851	0.903444	8674.6	−5.4942
BG_r	1	3146	3146	0.193442	0.789236	0.982678	8444.3	−5.3504
SV_r	4	3146	786.5	0.183193	0.751115	0.934308	7490.9	−4.7392
SC_r	1	3123	3123	0.12687	0.81301	0.93988	7647.2	−4.8819
SG_r	2	2892	1446	0.164097	0.656088	0.820185	6333.3	−4.3578
Panel C	**Size and financial leverage-sorted portfolios**							
BH_r	1	3146	3146	0.164176	0.815693	0.979869	8481.8	−5.3768
BL_r	2	3146	1573	0.152904	0.774975	0.927879	8889.6	−5.6309
SH_r	5	3146	629.2	0.149808	0.752564	0.902372	7656.9	−4.8421
SL_r	2	3146	1573	0.158383	0.799422	0.957805	7627.6	−4.8286
Panel D	**BM ratio and financial leverage portfolios**							
VH_r	4	3133	783.25	0.175013	0.694857	0.86987	7454.5	−4.7356
VL_r	4	3146	786.5	0.152379	0.800962	0.953341	7999.7	−5.0626
CH_r	1	3143	3143	0.139234	0.819289	0.958523	7823.5	−4.963
CL_r	1	3146	3146	0.146712	0.745216	0.891928	8578.1	−5.4354
GH_r	5	3146	629.2	0.141883	0.811456	0.953339	8139.0	−5.146
GL_r	5	3139	627.8	0.315049	0.664859	0.979908	7518.6	−4.7648

[a]Optimal number of Knots in the spline-GARCH model. [b]Number of observations per Knot in the spline-GARCH model. [c]ARCH effect in the spline-GARCH model. [d]GARCH effect in the spline-GARCH model

GARCH effect indicates that past volatility has an explanatory power on the current volatility. Moreover, sum of the ARCH and GARCH (α + β) coefficients provides us with a measure of volatility persistence which will increase (decrease) with time if the sum is greater (less) than unity. Table 4 reports the values of volatility persistence (α + β) which show that innovations to volatility of all portfolios decay with time since their value approaches to unity. However, degree of the volatility persistence varies slightly across single characteristic-sorted portfolios where volatility of the growth portfolio has the highest value of volatility persistence, 0.96 while the volatility of the core portfolio are less persistent, 0.94. With respect to the double characteristics-sorted portfolios, volatility persistence ranges from 0.82 (for SG portfolio) to 0.98 (for BG portfolio). In other words, shocks to volatility of big-growth (small-growth) portfolio takes much (less) time to die out than other portfolios.

5.3. Stationary Test

Table 5 presents the results of stationary test using the augmented dickey-fuller unit root test for the volatility series for the macroeconomic variables as well as the portfolio returns. All macroeconomic volatilities are stationary at level. With respect to the portfolio return volatility, the value, growth and low leverage portfolios (in panel A) as well as the volatilities of the big-value, big-core, and the small-value portfolios in panel B are stationary at the first difference. The volatilities of all portfolios in panel C have unit root at their levels which removed by taking the first difference. In panel D, the unit root appears in the volatilities series for the value-high, the value-low and the growth-high leverage portfolios.

5.4. Results of Regression Analysis

Since Ordinary least squares estimation could be sensitive to the presence of outliers, we follow Basistha and Kurov (2008) to estimate the regression in Equations (9) and (10) using the robust least squares model in order to maintains robustness with the existence of a large number of outliers. Tables 6 report the Robust least squares regression results based on Equations (9) and (10) respectively, for 23 different portfolios over the period July 2002-June 2015. Recall that, using Eq. (9), we estimate the impact of macroeconomic volatility on volatility of different characteristics-sorted portfolios regardless of impacts of financial crisis and political uncertainty. Comparably, Eq. (10) is augmented to include two dummy variables, to account for impact of both the global financial crisis and political instability during and post-revolution period.

The coefficient of *EGXVOL* is significant, positive for the volatilities of BIG, SMALL, CORE and HIGH financial leverage portfolios but is negative for the volatility of VALUE portfolio. Small portfolio volatility is more sensitive than big portfolio volatility to the *EGXVOL*. Both volatilities of growth and low leverage portfolios are insignificantly related to the EGX index volatility. In contrast, the coefficients of *EGXVOL* are always negative in the case of the double characteristics sorted portfolios, namely, the volatilities of big-value (BV), big-core (BC), small-value (SV), big-low leverage (BL), small-low Leverage (SL) and value-high leverage (VH) portfolios but it has a positive coefficient for the core-low (CL) leverage portfolio. These findings reveal that most double characteristics sorted portfolios tend to move

Table 5: Stationary test for independent variables and dependent variables (using ADF test*)

Macro variables	*CPIVOL*	*EGXVOL*	*FXVOL*	*M2VOL*	*NIRVOL*	*RPIVOL*	*TBVOL*
Level							
t-statistic	−12.07	−10.747	−12.116	−11.854	−12.369	−12.382	−5.2515
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel A	***Bvol***	***Svol***	***Vvol***	***Cvol***	***Gvol***	***Hvol***	***Lvol***
Level							
t-statistic	−6.81781	−5.82256	−1.58465	−6.43949	−0.02025	−6.27212	−1.96195
Prob.	0.0000	0.0000	0.4876	0.0000	0.9543	0.0000	0.3033
First difference							
t-statistic			−4.04738		−2.90068		−3.32338
Prob.			0.0016		0.0480		0.0158
Panel B	***BVvol***	***BCvol***	***BGvol***	***SVvol***	***SCvol***	***SGvol***	
Level							
t-statistic	−1.57117	−1.95771	−4.0841	−1.55617	−3.48394	−3.44964	
Prob.	0.4945	0.3053	0.0014	0.5023	0.0099	0.0109	
First difference							
t-statistic	−4.22898	−3.8502		−3.2614			
Prob.	0.0009	0.0032		0.0186			
Panel C	***BHvol***	***BLvol***	***SHvol***	***SLvol***			
Level							
t-statistic	−1.7613	−1.93498	−1.27817	−1.33769			
Prob.	0.3982	0.3155	0.6388	0.6107			
First difference							
t-statistic	−4.19881	−3.85683	−3.03933	−4.17386			
Prob.	0.0010	0.0031	0.0337	0.0011			
Panel D	***VHvol***	***VLvol***	***CHvol***	***CLvol***	***GHvol***	***GLvol***	
Level							
t-statistic	−1.06322	−1.59587	−3.4666	−6.55755	−1.62348	−3.64956	
Prob.	0.7291	0.4821	0.0104	0.0000	0.4680	0.0059	
First difference							
t-statistic	−4.17428	−2.87796			−3.899		
Prob.	0.0010	0.0505			0.0026		

*Augmented dickey-fuller unit root test use a null hypothesis that variable has a unit root

in opposite direction of the general volatility in the home stock market. In turn, these portfolios are more preferable than the single characteristic sorted ones since the former provides diversification opportunity for investors, especially who invest in the exchange traded funds (ETFs). However, in the presence of dummy variables reflecting effects of global financial crisis and political uncertainty, the *EGXVOL* coefficient lose its significance. This indicates that potential impact of uncertainty during financial crisis as well as during the political instability dominates the relationship between characteristic-sorted portfolios and market portfolio.

Arguably, Inflation volatility (*CPIVOL*) has no significant effect on volatilities of the single characteristics-sorted portfolios, except the growth portfolio (*Gvol*) has a positive coefficient of the inflation volatility. However, its impact on double sorted portfolios is in opposite directions where it has a positive sign for big-high leverage (*BHvol*) and growth-high leverage (*GHvol*) portfolios while it has a negative sign for the volatilities of small-value (*SVvol*), value-high leverage (*VHvol*) and value-low leverage (*VLvol*). Moreover, the *CPIVOL* coefficient has more significant relations in the presence of the dummy variables (financial crisis and political uncertainty) whereby it negatively affects the volatility of value portfolio (*Vvol*) and Big-value (*BVvol*) portfolio. More importantly, volatility of value stocks is more sensitive (regardless the sign) to the *CPIVOL* than the growth portfolio. Moreover, the volatility of small-value portfolio responds more significantly to the *CPIVOL* than the volatility of big-value portfolio. Similarly, value-high (*VHvol*) leverage portfolio is more sensitive than growth-high (*GHvol*) leverage portfolio. On the other hand, volatility of the growth stocks as well as the *BHvol* and *GHvol* portfolios increase with the inflation risk.

The coefficient of the Foreign exchange volatility (*FXVOL*) is positive, significant to low leverage (*Lvol*) portfolio, big-value (*BVvol*), big-low (*BLvol*) and small-low (*SLvol*) portfolio at 10 % level. By adding dummy variables, the FXVOL coefficient lose its significance to both the *BLvol* and *SLvol* portfolios while its impact on value-high leverage (*VHvol*) portfolio become significant, positive at 10% level. Typically, the earnings for exporting company are considerably influenced by the exchange rate and consequently volatility in exchange rate can result in volatile earnings which translated in the volatility of company's stock prices (Chinzara, 2011). This explanation is consistent with the flow oriented approach which assumes that exchange rate volatility will influence the international competitiveness of domestic companies and consequently affects their expected cash flows (Mlambo et al., 2013).

Volatility of real production growth (*RPGVOL*) has a positive, significant impact on growth (*Gvol*) portfolio, big-high (*BHvol*) leverage while it has negative, significant impacts on the big (*Bvol*), small (*Svol*) and high leverage (*Hvol*) portfolios as well

Table 6: Estimation results for the impact of macroeconomic volatility on characteristics-sorted portfolios

Portfolios	Eq. 9: Without dummy variables								Eq. 10: With dummy variables									
	Single characteristic-sorted portfolios																	
	Intercept	*EGXVOL*	*CPIVOL*	*FXVOL*	*RPIVOL*	*M2VOL*	*NIRVOL*	Rw-sq Prob[e]	Intercept	*EGXVOL*	*CPIVOL*	*FXVOL*	*RPIVOL*	*M2VOL*	*NIRVOL*	*DUMCRISIS*	*DUMPOLIT*	Rw-sq Prob[e]
Panel A																		
Bvol	0.00	0.000714	−0.021994	−0.003426	−0.003189	0.010922	−0.351832	0.118	0.00	0.000310	−0.010652	−0.003245	−0.002373	0.011694	−0.359694	0.000050	−0.000012	0.22
	0.00	(0.050)[a]	0.674	0.214	(0.031)[b]	(0.000)[c]	0.704	0.0000	0.00	0.388	0.826	0.204	(0.093)[a]	(0.000)[c]	0.676	(0.001)[c]	0.198	0.0000
Svol	0.00	0.003381	−0.041823	−0.016923	−0.011636	0.051341	−1.981355	0.108	0.00	0.001164	0.006658	−0.015633	−0.009552	0.057318	−1.624407	0.000274	−0.000015	0.23
	0.00	(0.033)[b]	0.854	0.159	(0.070)[a]	(0.000)[c]	0.624	0.0000	0.00	0.466	0.975	0.169	0.129	(0.000)[c]	0.671	(0.000)[c]	0.702	0.0000
Vvol	0.00	−0.00031	−0.025117	0.001669	−7.90E-05	−0.005668	0.466315	0.128	0.00	0.000022	−0.030702	0.001477	0.000257	−0.007721	−0.656868	−0.000040	−0.000013	0.50
	0.02	(0.035)[b]	0.235	0.134	0.895	(0.000)[c]	0.213	0.0000	0.00	0.862	(0.075)[a]	0.103	0.607	(0.000)[c]	(0.031)[b]	(0.000)[c]	(0.000)c	0.0000
Cvol	0.00	0.001751	−0.006512	−0.009902	−0.004676	0.025369	−1.239367	0.097	0.00	0.000526	0.012085	−0.008704	−0.004706	0.029655	−0.839844	0.000151	0.000022	0.22
	0.00	(0.037)[b]	0.957	0.119	0.169	(0.000)[c]	0.562	0.0000	0.00	0.534	0.916	0.148	0.157	(0.000)[c]	0.678	(0.000)[c]	0.303	0.0000
Gvol[d]		0.000000	0.000107	0.000000	0.000004	−0.000021	−0.000330	0.212		0.000000	0.000098	−0.000001	0.000003	0.000000	−0.000677	0.000000	0.000000	0.14
		0.140	(0.002)[c]	0.844	(0.001)[c]	(0.000)[c]	0.587	0.0000		0.188	(0.005)[c]	0.704	(0.006)[c]	0.338	0.277	0.486	0.942	0.0105
Hvol	0.00	0.001676	−0.055842	−0.007153	−0.007847	0.026489	−0.723022	0.119	0.00	0.000742	−0.020775	−0.007219	−0.005472	0.027865	−0.852998	0.000115	−0.000046	0.25
	0.00	(0.043)[b]	0.638	0.253	(0.019)[b]	(0.000)[c]	0.731	0.0000	0.00	0.363	0.850	0.214	(0.088)[a]	(0.000)[c]	0.662	(0.001)[c]	(0.027)b	0.0000
Lvol		0.000000	0.000052	0.000020	−0.000001	0.000003	0.001798	0.013		0.000000	0.000060	0.000019	−0.000001	0.000003	0.001614	0.000000	0.000000	0.03
		0.929	0.801	(0.072)[a]	0.857	(0.066)[a]	0.620	0.2959		0.939	0.774	(0.080)[a]	0.833	(0.053)[a]	0.659	0.512	0.527	0.4060
Panel B	Size and BM ratio-sorted portfolios																	
Bvvol	0.00	−0.000418	−0.041748	0.002861	0.000548	−0.011321	0.425158	0.161	0.00	−0.000100	−0.048439	0.002443	0.000491	−0.012708	0.241346	−0.000044	−0.000008	0.35
	0.06	(0.051)[a]	0.174	(0.077)[a]	0.527	(0.000)[c]	0.435	0.0000	0.00	0.630	(0.083)[a]	(0.097)[a]	0.545	(0.000)[c]	0.626	(0.000)[c]	0.140	0.0000
Bcvol	0.00	−0.000079	−0.006721	0.000500	−0.000079	−0.001130	0.124685	0.095	0.00	0.000005	-0.007616	0.000358	0.000033	−0.001602	0.071380	−0.000011	−0.000005	0.46
	0.01	(0.053)[a]	0.253	0.106	0.635	(0.000)[c]	0.231	0.0000	0.00	0.880	0.116	0.161	0.817	(0.000)[c]	0.406	(0.000)[c]	(0.000)c	0.0000
Bgvol[d]		−0.000008	−0.000036	−0.000014	0.000048	0.001081	−0.007919	−0.980		0.000002	0.002175	0.000014	0.000028	0.000051	−0.002157	−0.000007	−0.000009	0.41
		0.850	0.995	0.962	0.792	(0.000)[c]	0.937	0.0000		0.942	0.548	0.940	0.809	(0.096)[a]	0.973	(0.000)[c]	(0.000)c	0.0000
Svvol	0.00	−0.000996	−0.063018	0.002404	0.000226	−0.008791	−1.602004	0.304	0.00	−0.000234	−0.068183	0.002027	−0.000076	−0.009978	−1.291202	−0.000088	−0.000005	0.70
	0.03	(0.000)[c]	(0.055)[a]	0.165	0.807	(0.000)[c]	(0.006)[c]	0.0000	0.00	0.197	(0.006)[c]	0.117	0.916	(0.000)[c]	(0.003)[c]	(0.000)[c]	0.286	0.0000
Scvol[d]		−0.000037	−0.000468	−0.000055	−0.000148	0.001881	−0.023588	−3.645		0.000000	0.001500	−0.000004	0.000016	0.000028	−0.000703	−0.000003	−0.000004	−1.36
		0.274	0.918	0.819	0.316	(0.000)[c]	0.771	0.0000		0.989	0.410	0.968	0.785	(0.070)[a]	0.983	(0.000)[c]	(0.000)c	0.0000
Sgvol	0.00	0.005010	0.435094	0.001524	−0.041256	0.184036	7.369850	0.144	0.00	0.003275	0.617632	−0.006098	−0.014966	0.165251	4.376041	0.000138	−0.000611	0.45
	0.00	0.235	0.469	0.974	(0.016)[b]	(0.000)[c]	0.496	0.0000	0.00	0.366	0.204	0.871	0.295	(0.000)[c]	0.617	0.369	(0.000)c	0.0000

Continued	Eq. 9: Without dummy variables								Eq. 10: With dummy variables									
Panel C	Size and financial leverage-sorted portfolios																	
	Intercept	*EGXVOL*	*CPIVOL*	*FXVOL*	*RPIVOL*	*M2VOL*	*NIRVOL*	Rw-sq Prob[e]	Intercept	*EGXVOL*	*CPIVOL*	*FXVOL*	*RPIVOL*	*M2VOL*	*NIRVOL*	*DUMCRISIS*	*DUMPOLIT*	Rw-sq Prob[e]
Bhvol[d]		8.71E-07	0.000246	−9.31E-07	0.000008	−0.00005	−0.000847	0.212		0.000001	0.000231	−0.000002	0.000008	−0.000001	−0.001453	0.000000	0.000000	0.16
		0.124	(0.001)[c]	0.818	(0.002)[c]	(0.000)[c]	0.534	0.0000		0.179	(0.004)[c]	0.669	(0.003)[c]	0.311	0.301	0.569	0.696	0.0049
	0.00	−0.00006	−0.005227	0.000412	−6.55E-05	−0.000831	0.095408	0.092	0.00	0.000004	−0.005937	0.000297	0.000034	−0.001209	0.055220	−0.000008	−0.000004	0.46
	0.00	(0.058)[a]	−0.262	(0.093)[a]	0.618	(0.000)[c]	0.248	0.0000	0.00	0.892	0.123	0.143	0.761	(0.000)[c]	0.418	(0.000)[c]	(0.000)[c]	0.0000
Shvol	0.00	−0.000142	0.004797	0.000567	−0.000258	0.004955	−0.647168	0.052	0.00	0.000125	−0.004544	−0.000147	−0.000195	0.003449	−0.080488	−0.000036	−0.000012	0.50
	0.70	0.302	0.808	0.585	0.642	(0.000)[c]	(0.064)[a]	0.0000	0.00	0.221	0.742	0.839	0.628	(0.000)[c]	0.742	(0.000)[c]	(0.000)c	0.0000
Slvol	0.00	−0.000354	−0.030461	0.002166	−6.44E-05	−0.00637	0.517452	0.125	0.00	−0.000006	−0.034398	0.001663	0.000188	−0.008103	0.294848	−0.000044	−0.000014	0.44
	0.06	(0.042)[b]	0.222	(0.099)[a]	0.927	(0.000)[c]	0.242	0.0000	0.00	0.972	0.101	0.132	0.758	(0.000)[c]	0.428	(0.000)[c]	(0.000)[c]	0.0000
Panel D	BM ratio and financial leverage-sorted portfolios																	
Vhvol	0.00	−0.00084	−0.049035	0.00223	0.000201	−0.010955	−1.349193	0.327	0.00	−0.000205	−0.053913	0.001931	−0.000030	−0.011590	−1.006346	-0.000067	−0.000003	0.67
	0.01	(0.000)[c]	(0.092)[a]	0.145	0.806	(0.000)[c]	(0.009)[c]	0.0000	0.00	0.187	(0.010)[b]	(0.080)[a]	0.961	(0.000)[c]	(0.007)[c]	(0.000)[c]	0.376	0.0000
Vlvol	0.00	−0.000292	−0.050175	0.00175	0.000142	−0.010393	−1.044314	0.198	0.00	0.000068	−0.055401	0.001435	−0.000220	−0.011230	−0.910673	−0.000049	−0.000001	0.50

(Contd...)

Table 6: (*Continued*)

Panel D	BM ratio and financial leverage-sorted portfolios																	
	0.02	0.113	(0.058)[a]	0.209	0.849	(0.000)[c]	(0.026)[b]	0.0000	0.00	0.663	(0.009)[c]	0.196	0.719	(0.000)[c]	(0.015)[b]	(0.000)[c]	0.874	0.0000
Chvol[d]		−3.56E-05	−0.00049	−5.40E-05	−0.000151	0.001873	−0.023969	−3.653		0.000000	0.000979	−0.000003	0.000019	0.000028	−0.000840	−0.000003	−0.000004	−1.61
		0.296	0.915	0.825	0.309	(0.000)[c]	0.770	0.0000		0.984	0.574	0.973	0.732	(0.062)[a]	0.978	(0.000)[c]	(0.000)[c]	0.0000
Clvol	0.00	0.001657	−0.003909	−0.009544	−0.004245	0.023863	−1.200058	0.096	0.00	0.000488	0.012924	−0.008340	−0.004425	0.028080	−0.794371	0.000144	0.000025	0.22
	0.00	(0.038)[b]	0.973	0.114	0.189	(0.000)[c]	0.554	0.0000	0.00	0.543	0.905	0.144	0.161	(0.000)[c]	0.679	(0.000)[c]	0.221	0.0000
Ghvol	0.00	4.80E-05	0.046973	−0.000257	0.000143	0.016147	−0.148568	0.296	0.00	0.000200	0.046520	−0.000350	0.000142	0.015814	−0.189978	−0.000020	−0.000001	0.31
	0.04	0.785	(0.063)[a]	0.846	0.841	(0.000)[c]	0.740	0.0000	0.09	0.295	(0.072)[a]	0.797	0.850	(0.000)[c]	0.678	(0.017)[b]	0.762	0.0000
Glvol		−0.009375	4.506167	0.107377	0.412686	−6.427802	113.0027	−0.060		0.029259	−4.037017	−0.022342	0.101881	0.002137	37.718930	0.005663	−0.036941	0.50
		0.949	0.820	0.918	0.517	(0.000)[c]	0.747	0.0000		0.756	0.752	0.974	0.804	0.984	0.868	0.256	(0.000)[c]	0.0000

Panel A includes: Big (B), Small (S), Value (V), Core (c), Growth (G), High leverage (H), Low leverage (L). Panel B includes: Big-value (BV), Big-core (BC), Big-growth (BG), Small-value (SV), Small-core (SC), and Small-growth (SG). Panel C includes: Big-high leverage (BH), Big-low leverage (BL), Small-high leverage (SL), Small-low leverage (SL). Panel D includes: Value-high leverage (VH), Value-low leverage (VL), Core-high leverage (CH), Growth-high leverage (GH), Value-low leverage (VL), Core-low leverage (CL), Growth-low leverage (GL).[a,b,c] stand for significance levels at 10%, 5%, and 1%, respectively. dSince the model suffers from autocorrelation, all variables subject to the first difference in the regression to remover the autocorrelation problem and consequently there is no intercept term. [e]Stands for the probability of Rn-squared statistics. For volatilities of each macroeconomic variables as well as for each portfolio, *vol* is added to their names

as the small-growth (*SGvol*) portfolio. Notably, the *Svol* portfolio is more sensitive to the *RPGVOL* than the *Bvol* portfolios. In the presence of dummy variables, the *RPGVOL* will lose its significant impact on the *Svol* and the *SGvol* portfolio. The results indicate that an increase in the production volatility will increase volatility of the growth portfolio as well as volatility of the big-high leverage portfolio but it will depress volatility of the big portfolio and the high leverage portfolio. The results reveal that production volatility affects strongly the volatility of cash flows for growth firms and big firms with high leverage ratio. In contrast, it has a negative effect on the uncertainty of cash flows for big firms as well as high leverage firms. This negative relation can be explained as good news about production volatility can decrease volatility of stock prices for the big firms and high leverage firms while bad news about the production volatility tend to raise volatility of their stock prices. The good news refer to increase/stability in production growth but bad news imply decrease/instability in the production growth.

The credit channel of monetary policy affects firms in the stock market through two channels; bank loan channel and balance sheet channel; the former refers to the impact of bank credit supply on bank-dependent borrowers while the latter considers how the creditworthiness of firms changes according to procyclical changes in the firms' balance sheet quality (Basistha and Kurov, 2008). Coefficient of money supply (*M2vol*) volatility is significant at 1% to all portfolios but in different signs. In the case of the single characteristic-sorted portfolios, all their volatilities (except both value and growth portfolios) respond positively to the M2 volatility. As expected, the volatilities of small, value and high leverage portfolios are more sensitive than the volatilities of big, growth and low leverage portfolios to the M2 volatility. Documenting that small portfolio volatility is more sensitive to M2 volatility than big portfolio volatility is an evidence for the bank loan channel of monetary policy transmission. This result can be explained as the small firms have less access to different sources of funds and thus are considered as bank-dependent borrowers, they are more sensitive to uncertainty about the money supply than big firms. Moreover, the higher response of value stock than growth stocks to the *M2vol* confirms that validity of the balance sheet channel of monetary policy transmission. The *BVvol*, *BCvol*, *SVvol*, *BHvol*, *BLvol*, *SLvol*, *VHvol*, *VLvol* and *GLvol* portfolios respond negatively to M2 volatility while the *BGvol*, *SCvol*, *SGvol*, *SHvol*, *CHvol*, *CLvol* and *GHvol* portfolios react positively to the M2 volatility. In terms of magnitude, the *Svol* portfolios (among single characteristic sorted portfolios) and the *SGvol* portfolios (among double characteristics sorted portfolios) are the most sensitive to the Money supply volatility. This high magnitude strengthens the credit channel transmission of monetary policy because small firms, especially if they are growth, with limited sources of finance and then are more affected by tight credit policy. Clearly, the money supply volatility is the most significant independent variable for all different portfolios. However, in presence of the dummy variables, this significance will be lost for only 3 out of 23, namely the *Gvol* portfolio as well as the *BHvol* portfolio and the *GLvol* portfolio as reported in Table 6.

The interest rates volatility (*NIRVOL*), regardless of the effects of financial crisis and political uncertainty, has no relationship with volatility of the single characteristic-sorted volatility. However, it negatively affects the volatility of *SVvol*, *SHvol*, *VHvol* and *VLvol* portfolios. On the other hand, by adding the dummy variables to the estimation, the *NIRvol* coefficient to the *Vvol* portfolio become significant and conversely the *NIRVOL* coefficient to *SHvol* portfolio become insignificant. Obviously, the *NIRvol* is associated negatively with the volatility of four portfolios (*Vvol* portfolio, *SVvol*, *VHvol* and *VLvol* portfolios) with high magnitudes. Moreover, these four portfolios witness the highest explanatory power in terms of R^2. This documented negative relationship between interest rate risk and volatility of characteristics-sorted portfolios are consistent with prediction of Zhang et al. (2009) who classify small firms and value firms as low-duration firms which suffer from high leverage and cash flow uncertainty and thus their returns will be affected poorly when short-term interest rates are high. On the other side, most portfolios have no significant relationship with the interest rate volatility and in turn these portfolios can be considered as hedge investments against the interest rate risk. Alternatively, the series of interest rates is normally distributed and experiences low volatility during the sample period, as shown in Table 2. This imply low uncertainty about interest rates and investors rebalance their portfolios less excessively to the expected volatility in interest rates.

Volatility of all single characteristics-sorted portfolios tend to increase during the financial crisis period, except volatility of value portfolio tends to decrease. Both growth and low leverage portfolios have no significant coefficient of the financial crisis dummy variable. Despite of low magnitudes, the small, value, and high financial leverage portfolios tend to be more volatile than the big, growth and low financial leverage portfolios during the financial crisis period. Surprisingly, all the double characteristics-sorted portfolios (except *CLvol* portfolio) experience less volatility during the crisis period. Moreover, the *SGvol*, *BHvol* and *GLvol* portfolios do not respond significantly to the financial crisis.

To take the impact of the political uncertainty after the Egyptian revolution into account, Eq. (10) uses a dummy variable for the period January 2011 to July 2014. Most single characteristic-sorted portfolios do not influenced by the political instability. Similarly, seven double characteristics-sorted portfolios (i.e., *BVvol*, *SVvol*, *BHvol*, *VHvol*, *VLvol*, *CLvol* and *GHvol*) have no significant relation with the dummy variable reflecting political uncertainty. In contrast, both the *Vvol* and *Hvol* portfolios as well as the *BCvol*, *BGvol*, *SCvol*, *SGvol*, *BLvol*, *SHvol*, *SLvol*, *CHvol* and *GLvol* portfolios tend to be less volatile during the political uncertainty. This implies that the precautionary procedures adopted by the EGX could efficiently reduce the expected excessive (low-frequency) volatility in the Egyptian stock market post the revolution in 2011.

Table 6 reports the explanatory power of the macroeconomic volatility for explaining volatility of the characteristics-sorted portfolios regardless the potential effects of financial crisis and political uncertainty (post the 25 January 2011 revolution). In case of single characteristic-sorted portfolios, the macroeconomic volatility can explain 21% of changes in the volatility of growth portfolio. In case of double characteristics-sorted portfolios; the macroeconomic volatility explains 30% and 33% of variations in the volatility of small-value (*SVvol*) portfolio and value-high leverage (*VHvol*) portfolio, respectively. This indicates that these portfolios are more efficient than other portfolios because their volatility in stock prices reflect contemporaneous volatility of the macroeconomic variables.

Taking into account the effects of global financial crisis as well as uncertainty associated with political instability due to the revolution in 25 January 2011, the explanatory power of the macroeconomic volatility is considerably improved as reported in Table 6. This finding is consistent with Chinzara (2011) who finds that explanatory power of the macroeconomic volatility to explain variations in stock market volatility has increased from 25% to 80% when he includes a dummy variable reflecting the global financial crisis. The reported R_w^2 values for the single characteristic-sorted portfolios reveal that 50% of variations in volatility of the value portfolio, is explained by the macroeconomic volatility in addition to uncertainty during financial crisis period as well as political instability period. On the other hand, the macroeconomic volatility in addition to the dummies can explain 70% and 67% of changes in the *SVvol* and *VHvol* portfolios, respectively while explain 50% of variations in each of *SHvol*, *VLvol* and *GLvol* portfolios. Recall that high R_w^2 values imply that these portfolios are more efficient and investors should care more with the macroeconomic variables when they construct and rebalance their investment portfolios.

Most importantly, we adopt two possible explanations for the documented relationship between the macroeconomic uncertainty and portfolio volatility. The first explanation is related to the information flow. High macroeconomic uncertainty can adversely and asymmetrically affect the corporate decisions with respect to their investment rates (Beaudry et al., 2001), the efficient allocation of firms' resources between capital spending and short-term liquidity needs (Baum et al., 2006) and changes in financial leverage (Baum et al., 2010). More specifically, corporate decisions are more homogenous, for example in their investment growth rates and demand for capital during periods of high macroeconomic uncertainty. This homogenous across firms implies few considerable actions/decisions can be taken and consequently low new information flow will be available in the market, thus investors are less likely to rebalance their portfolios which eventually results in low trading volume. Based on the well documented positive relationship between trading volume and volatility (Karpoff, 1987; Verma and Verma, 2007; Yang and Wu, 2011), the low portfolio rebalancing is associated with low trading volumes which results in less volatility level. Conversely, low macroeconomic uncertainty is associated with heterogeneity across firms regarding investments and demand for capital. Therefore, much new information will be available about many firms and investors respond to that information by rebalancing excessively their portfolios accordingly. This increase in trading volume results in a greater volatility.

The second explanation is related to the volatility feedback hypothesis whereby investors react to bad news by requiring higher expected returns (i.e., risk premium) as a compensation for the increased inherent risk of holding stocks. Based on the assumption that a positive relation between volatility and expected returns, the increase in future volatility feeds back and decreases contemporaneous returns (Gospodinov and Jamali, 2014). On the other hand, macroeconomic uncertainty can be either positive (good) or negative (bad) uncertainty. A recent study by Segal et al. (2015) documents that stock returns respond positively (negatively) to the good (bad) macroeconomic uncertainty. Although both uncertainties contribute positively to the risk premium, their covariance may affect negatively the risk premium (Segal et al., 2015). Therefore, if the interaction of bad and good uncertainties contributes negatively to the risk premium required by investors to hold stocks, their prices (returns) will increase and subsequently volatility will decrease.

6. CONCLUSION AND RECOMMENDATIONS

This paper seeks to examine the asymmetric response of volatility in the characteristics-sorted portfolios to the macroeconomic volatility based on Egyptian data covering the period July 2002-June 2015. The paper uses three characteristics; size, BM ratio and financial leverage so as to sort the most active stocks into corresponding characteristics mimicking portfolios. We adopts the spline-GARCH (1,1) model to derive the low-frequency volatility of portfolio returns and then regress it against the monthly volatility in macroeconomic variables. The main hypothesis of current study is that a single factor mimicking portfolios tend to behave asymmetrically in different periods of time, thus forming portfolios on different characteristics may gain some diversification.

The returns and volatility statistics during different periods show considerable inferences. As expected, returns on small, value and high leverage portfolios outperform returns on big, growth and low leverage portfolios. Similarly, the associated risks of the three portfolios (small, value and high leverage portfolios) are greater than risks of the big, growth and low leverage portfolios. Moreover, the statistics indicates that constructing portfolios based on different characteristics rather than based on single ones will provide investors with higher returns at different levels of risk. Stocks characterized as small-core-high leverage or characterized as small-value-high leverage are more likely to earn higher returns under normal market conditions. Holding a small-value-low leverage portfolio earns positive returns during the financial crisis while holding a big-value-low leverage portfolio make investors less sensitive to the political events than other portfolios.

Volatility of value stocks either big or small; highly levered or low levered, are more likely to decrease when inflation uncertainty is high. Conversely, volatility of growth stocks, either big or small and especially highly levered, are more likely to increase when the inflation uncertainty is high. Put it in different way, volatility of the *BVH*, *BVL*, *SVH* and *SVL* portfolios are more likely to negatively related to the *CPIVOL* while volatility of the BGH and SGH portfolios are more likely to positively related. In general, the inflation volatility has significant relationship with only 8 out of the 23 portfolios. Therefore, the remaining 15 portfolios are expected to provide market participants with a hedge against the inflation risk. Managers of the firms characterized with high growth opportunities should not take considerable decisions during period of high inflation uncertainty because their shareholders may respond more aggressively to such decisions. Both big-value firm and value-high leverage firms usually have large portion of their cash flow from exports, thus uncertainty about foreign exchange would be translated directly in high volatility of the stock prices. Thus, both managers and investors in these firms should hedge against foreign exchange risk. Otherwise, investors can diversify their investments through take positions in other characteristics-sorted portfolios having weak relation with the foreign exchange volatility. Moreover, the weak relationship between the foreign exchange volatility and the volatility of characteristics-sorted portfolios provides foreign investors with hedging opportunities whereby avoid foreign exchange risks. The volatility of production growth is strongly associated with the volatility of single characteristic-sorted portfolios but is weakly associated with the volatility of double characteristics-sorted portfolios. The findings reveal that all characteristics-sorted portfolios respond significantly asymmetrically to the money supply volatility. In terms of magnitude, the *Svol* portfolios (among single characteristic sorted portfolios) and the *SGvol* portfolios (among double characteristics sorted portfolios) are the most sensitive to the Money supply volatility. Most portfolios have no significant relationship with the interest rate volatility and in turn these portfolios can be considered as hedge investments against the interest rate risk. We adopt two possible explanations to the documented effect of macroeconomic volatility on volatility of the characteristics-sorted portfolios; information flow and volatility feedback hypothesis. The findings also support role of the precautionary procedures imposed to limit excessive volatility after the January, 2011 revolution.

Results have important policy implications. Policy makers can use the exchange rate policy as a tool to attract foreign investments. Uncertainty associated with the money supply is the most dominant source of portfolio return volatility. Thus, monetary policymakers should concentrate on the credit supply channel of monetary policy transmission more than interest rate channel when formulating the monetary policy. On the other hand, they can affect stock return volatility through better transparency and implementation of forward guidance. In turn, the investors can forecast accurately the monetary actions. Moreover, the Egyptian exchange should develop new financial instruments such as volatility swaps to hedge investors against monetary policy shocks.

This paper extends new ideas for future researches. Firstly, the relationship between macroeconomic variables and style mimicking portfolios in the framework of the first moment (returns) should be examined in emerging stock markets such as Egyptian stock market. Secondly, investigating the relationship between returns and volatility of the characteristics-sorted portfolios to the investor sentiment. Thirdly, examining the effect of the market microstructure (such as different trading mechanisms and types of investors) on returns and volatilities of the characteristics mimicking portfolios.

REFERENCES

Adrian, T., Rosenberg, J. (2008), Stock returns and volatility: Pricing the short-run and long-run components of market risk. The Journal of Finance, LXIII(6), 2997-3030.

Azad, A.S., Fang, V., Wickramanayake, J. (2011), Low-frequency volatility of yen interest rate swap market in relation to macroeconomic risk. International Review of Finance, 11(3), 353-390.

Banz, R.W. (1981), The relationship between return and market value of common stocks. Journal of Financial Economics, 9, 3-18.

Barnard, K.J., Bunting, M.B. (2015), Value and size investment strategies during the global financial crisis: Evidence from the South African equity market. South African Journal of Accounting Research, 29(2), 177-196.

Basistha, A., Kurov, A. (2008), Macroeconomic cycles and the stock market's reaction to monetary policy. Journal of Banking and Finance, 32, 2606-2616.

Basu, S. (1977), Investment performance of common stocks in relation to their price-earnings ratios: Atest of the efficient market hypothesis. The Journal of Finance, 32(3), 663-682.

Baum, C.F., Caglayan, M., Ozkan, N., Talavera, O. (2006), The impact of macroeconomic uncertainty on non-financial firms' demand for liquidity. Review of Financial Economics, 15, 289-304.

Baum, C., Chakraborty, A., Liu, B. (2010), The impact of macroeconomic uncertainty on firms' changes in financial leverage. International Journal of Finance and Economics, 15, 22-30.

Beaudry, P., Caglayan, M., Schiantarelli, F. (2001), Monetary instability, the predictability of prices, and the allocation of investment: An empirical investigation using U.K. Panel data. The American Economic Review, 91(3), 648-662.

Black, A.J. (2006), Macroeconomic risk and the Fama-French three-factor model. Managerial Finance, 32(6), 505-517.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 31, 307-327.

Cakici, N., Fabozzi, F.J., Tan, S. (2013), Size, value, and momentum in emerging market stock returns. Emerging Markets Review, 16, 46-65.

Carhart, M.M. (1997), On persistence in mutual fund performance. The Journal of Finance, LII(1), 57-82.

Cenesizoglu, T. (2011), Size, book-to-market ratio and macroeconomic news. Journal of Empirical Finance, 18, 248-270.

Chan, H.W., Faff, R.W. (2005), Asset pricing and the illiquidity premium. The Financial Review, 40, 429-458.

Chen, N.F., Roll, R., Ross, S.A. (1986), Economic forces and the stock market. The Journal of Business, 59(3), 383-403.

Chinzara, Z. (2011), Macroeconomic uncertainty and conditional stock market volatility in South Africa. South African Journal of Economics, 79(1), 27-49.

Choe, H., Masulis, R.W., Nanda, V. (1993), Common stock offerings across the business: Theory and evidence. Journal of Empirical Finance, 1, 3-31.

Christie, A.A. (1982), The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of Fmanclal Economics, 10, 407-432.

Connor, G. (1995), The three types of factor models: A comparison of their explanatory power. Financial Analysts Journal, 51(3), 42-46.

Cowen, T. (2009), A simple theory of the financial crisis; Or, why fischer black still matters. Financial Analysts Journal, 65(3), 17-20.

EGX. (2008), Annual Report. Cairo: The Egyptian Exchange.

EGX. (2009), Annual Report. Cairo: The Egyptian Exchange.

Ehrmann, M., Fratzscher, M. (2004), Taking stock: Monetary policy transmission to equity markets. Journal of Money, Credit, and Banking, 36(4), 719-737.

Elton, E.J., Gruber, M.J., Brown, S.J., Goetzmann, W.N. (2014), Modern Portfolio Theory and Investment Analysis. 9th ed. New York: JohnWiley & Sons, Inc.

Engle, R. (1993), Statistical models for financial volatility. Financial Analysts Journal, 49(1), 72-78.

Engle, R.F., Lee, G. (1999), A long run and short run component model of stock return volatility. In: Engle, R.F., White, H, editors. Cointegration, Causality, and Forecasting: A Festschrift in Honour of Clive W. Oxford: Oxford University Press. p475-497.

Engle, R.F., Rangel, J.G. (2008), The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. The Review of Financial Studies, 21(3), 1187-1222.

Engle, R.F., Ghysels, E., Sohn, B. (2013), Stock market volatility and macroeconomic fundamentals. The Review of Economics and Statistics, 95(3), 776-797.

Fama, E., French, K. (1989), Business conditions and expected returns on stocks and bonds. Journal of Financial Economics, 25, 23-49.

Fama, E., French, K.R. (1993), Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33, 3-56.

French, K.R., Schwert, G.W., Stambaugh, R.F. (1987), Expected stock returns and volatility. Journal of Financial Economics, 19, 3-29.

Girardin, E., Joyeux, R. (2013), Macro fundamentals as a source of stock market volatility in China: A GARCH-MIDAS approach. Economic Modelling, 34, 59-68.

Gospodinov, N., Jamali, I. (2014), The response of stock market volatility to futures-based measures of monetary policy shocks. International Review of Economics and Finance, 37, 1-13.

Gulen, H., Xing, Y., Zhang, L. (2011), Value versus growth: Time-varying expected stock returns. Financial Management Association International, 40(2), 381-407.

Hu, Z. (1995), Stock Market Volatility and Corporate Investment. Research Department. International Monetary Fund.

Jones, C.M., Lamont, O., Lumsdaine, R.L. (1998), Macroeconomic news and bond market volatility. Journal of Financial Economics, 47, 315-337.

Kang, J., Kim, T.S., Lee, C., Min, B.K. (2011), Macroeconomic risk and the cross-section of stock returns. Journal of Banking and Finance, 35, 3158-3173.

Karpoff, J.M. (1987), The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis, 22(1), 109-126.

Kontonikas, A., Kostakis, A. (2013), On monetary policy and stock market anomalies. Journal of Business Finance and Accounting, 40(7-8), 1009-1042.

Li, X., Brooks, C., Miffre, J. (2009), The value premium and time-varying volatility. Journal of Business Finance and Accounting, 36(9-10), 1252-1272.

Liu, S., Tang, T., McKenzie, A.M., Liu, Y. (2015), Low-frequency volatility in China's gold futures market and its macroeconomic determinants. Mathematical Problems in Engineering, 2015, 1-8.

Mirza, N., Saeed, M.S., Rizvi, K.A. (2013), The pricing of size, book to market and financial leverage in euro stocks. Ekonomska Istraživanja-Economic Research, 26(1), 1-16.

Mlambo, C., Maredza, A., Sibanda, K. (2013), Effects of exchange rate volatility on the stock market: A case study of South Africa. Mediterranean Journal of Social Sciences, 4(14), 561-570.

Morelli, D. (2002), The relationship between conditional stock market volatility and conditional macroeconomic volatility empirical evidence based on UK data. International Review of Financial Analysis, 11, 101-110.

Murtazashvilia, I., Vozlyublennaiab, N. (2013), When do characteristics-sorted factors mechanically. Journal of International Financial Markets, Institutions and Money, 25, 119-143.

Olsen, R.A. (1998), Behavioral finance and its implications for stock-price volatility. Financial Analysts Journal, 54(2), 10-18.

Perez-Quiros, G., Timmermann, A. (2000), Firm size and cyclical variations in stock returns. The Journal of Finance, 55(3), 1229-1262.

Ramadan, I.Z. (2013), Dividend policy and price volatility. Empirical evidence from Jordan. International Journal of Academic Research in Accounting, Finance and Management Sciences, 3(2), 15-22.

Raunig, B., Scharler, J. (2011), Stock Market Volatility, Consumption and Investment; An Evaluation of the Uncertainty Hypothesis Using Post-War U.S. Data. Oesterreichische Nationalbank.

Rosenberg, B., Reid, K., Lastein, R. (1985), Persusasive evidence of market inefficiency. The Journal of Portfolio Management, 11, 9-16.

Ross, S.A. (1976), The arbitrage theory of capital asset pricing. Journal of Economic Theory, 13(3), 341-360.

Schwert, G.W. (1989), Why does stock market volatility change over time? The Journa of Finance, 44(5), 1115-1153.

Segal, G., Shaliastovich, I., Yaron, A. (2015), Good and bad uncertainty: Macroeconomic and financial market implications. Journal of Financial Economics, 117, 369-397.

Shaker, M.A., Elgiziry, K. (2014), Comparisons of asset pricing models in the egyptian stock market. Accounting and Finance Research, 3(4), 24-30.

Vassalou, M. (2000), The Fama-French Factors as Proxies for Fundamental Economic Risks. Columbia Business School. Center on Japanese Economy and Business.

Verma, R., Verma, P. (2007), Noise trading and stock market volatility. Journal of Multinational Financial Management, 17, 231-243.

West, K.D. (1988), Dividend innovations and stock price volatility. Econometrica, 56(1), 37-61.

Yang, A.S., Wu, M.L. (2011), Exploring the relationship between investor sentiment and price volatility. Quantitative Finance, 11(6), 955-965.

Zhang, Q.J., Hopkins, P., Satchell, S.E., Schwob, R. (2009), The link between macro-economic factors and style returns. Journal of Asset Management, 10, 338-355.