Effect of dividend policy on stock price volatility in the Dow Jones U.S. index and the Dow Jones islamic U.S. index: evidences from GMM and quantile regression

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Abstract

The relationship between stock price volatility and dividend policy remains a "puzzle" with conflicting evidences. The objective of this study is to attempt to shed light on this debate with the help of relatively advanced GMM methods and quantile regressions on the stocks listed in the Dow Jones U.S. Index and Islamic stocks based on the Dow Jones Islamic U.S. Index. Our data is unbalanced panel data consisting of two samples for all stocks (2456 companies) and Islamic stocks (589 companies) in the Dow Jones U.S. Index from the year 2005 to 2017. Our main findings suggest that dividend policy in both samples contributes a minor component to explaining stock price volatility and is becoming less relevant for the overall market. However, dividend yield shows positive relationship with stock price volatility when analyzed based on each class of stocks in the Dow Jones Islamic U.S. Index. Thus there could be a clientele effect in each class of stock for Islamic stocks. It is hoped that the findings of this study would contribute to dividend policy literature and Islamic equity literature.

Keywords: Dividend policy, stock price volatility, Islamic U.S. index, GMM, Quantiles

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1. Introduction

Dividend policy stands as an important factor in corporate financing decision in choosing to maximize shareholder value by either distributing dividend or retaining cash for future growth, and/or otherwise respond to the heterogenous preferences of market participants on the ideal dividend payout. Moreover, investors' eventual justification for any business to have any value at all is strictly tied to its ability to pay dividends either now or in the future in one form or another such as, a backdoor return to shareholders as is the case with stock repurchase plans. Therefore, dividend policy is argued to have direct effect on a company's value and market participants' behavior, which is reflected in the stock price volatility. Comprehensive theories and empirical investigations have been researched upon the topic; nonetheless, the effect of dividend policy and stock price volatility remains inconclusive.

Several corporate finance theories lay frameworks for the important implications of behavior of firm's dividend payout policy, starting with the prominent theory by Modigliani-Miller framework (1961) of the dividend irrelevant theory and the Efficient Market Hypothesis (EMH). These theories propose that the effects of dividend policy on stock price are null, and stock prices move independently of dividend policy under assumptions of EMH. Nevertheless, the theories are criticized for the unrealistic assumptions; thus, several counter theories approving the relevancy of dividend policy on stock price movement include clientele theory, "bird in hand" theory, agency theory, signaling theory, ownership structure and subsidiary factors. Since the turn of the new decade after the 2008 crisis and the rise of cash abundant technological companies, the testaments of these two camps of theories are remaining to be seen with support from empirical evidence on both sides.

The empirical evidence on the impact of dividend policy and stock price volatility show conflicting results based upon different timeframes and areas of studies. The empirical results obtained previously are based on static assumption of the models, which restrict a more robust reflection of highly dynamic movement of stock markets. Moreover, none of the prior studies investigate the relationship in the context of Islamic stocks.

Islamic equity has been gaining substantial interest due to the global demand for ethical investment amongst Muslim and non-Muslim investors. The unique characteristics of Islamic stocks lied in their screening criteria, which demand compliance with Islamic principles including limited interest-bearing financial transactions, limited leverage ratio, and lawful (halal) and ethical activities in firms' core business. The screening criteria should provide potential diversification advantage theoretically due to lower systemic risks and higher price stability. Recent studies also found support for stability (Iqbal et al., 2010, Al-Khazali et al. 2014; Jawadi et al. 2014), but mixed results for long-term benefit of Islamic equity for diversification (Saiti et al. 2016; Dewandaru et al. 2014; Ajmi et al. 2014; Hammoudeh et al. 2014). In addition, there is still scarce empirical support on Islamic stocks' dividend policy and their price volatility; thus, studying dividend policy in Islamic equity context could provide an insightful impact on the stability of Islamic stocks and implication for diversification benefits to this group of investors.

The connection between dividend policy and stock price volatility has been an on-going debate on both academic and stock market participants, despite numerous empirical investigations. Moreover, Islamic stocks is claimed to provide greater stability of returns on evidence on correlation between the individual stock price with other assets along with the whole market. There is yet no empirical evidence on the Islamic stocks' stability based on dividend policy. Therefore, the objective of this paper is to attempt to shed light on both topics testing both conventional and Islamic equity with the use of dynamic methods including generalized method of moments (GMM), and quantile regressive models.

In this paper, we investigate stocks listed in the Dow Jones U.S. index, which fitted the criteria for testing both pre-and-post 2008 financial crisis and inclusion of technological companies. The Islamic equity screening criteria for the stocks in the index is based the Dow Jones Islamic Index U.S. as the second subset of the sample deduced from the Dow Jones U.S. index. We found that dividend in both all stocks and Islamic stocks in the Dow Jones U.S. index has become less relevant especially in the case of dividend payout. Dividend yield, although not significant for the whole sample, shows positive relationship applying quantile regression, which indicates relationship for each class of stock according to the percentage point of quantiles of stock price volatility.

The paper contributes as follow:

1. The study provides new evidence on the dividend policy literature with the use of GMM estimators and quantile regressions
2. The findings in this study provide new insight and recommendations of both companies and investors in the Dow Jones U.S. index in anticipation of higher price volatility in changing of higher dividend yield especially for Islamic stocks.

3. The study added to the literature on stability and long-term diversification of Islamic equity.

The paper is structured as follows: chapter 2 present the reviews of related theories and empirical evidences from the literatures, chapter 3 outlines the methodology and the sample data, chapter 4 discusses the empirical results using different methods for robustness checks, and lastly, chapter 5 concludes the paper.

2. Literature Review

Modigliani-Miller (MM) framework and EMH: Dividend Irrelevant Theory

According to Miller & Modigliani (1961), corporate dividends are irrelevant to their stock price volatility under the condition of no tax, no transaction cost, EMH, no information asymmetry, investors are rational, and no agency issue. They argued that the irrelevant effects of dividend policy are such that stock prices move independently of dividend policy. Shareholders may sell their shares for higher cash payments, and they can re-invest dividends if they prefer lower cash positions. Thus, it is instead the company's earnings and its investment policy that figure the future cash flows and retained earnings, which should be affecting the stock price. Brennan (1971), Black & Scholes (1974), and Hakansson (1982) have supported MM on different markets of the world and concurred that dividends are irrelevant to stock prices. Fama & French (2001) indicated a general tendency for US-listed firms to become less likely to pay dividends; partly due to the listing of newer entities pursuing growth-oriented strategies which require extensive cash resources.

However, the assumptions of the dividend irrelevant theory were criticized to be a far cry from the reality of any stock market. The earlier work by Gordon (1963) has challenged dividend irrelevancy theory with the empirical findings that dividend policy does have an impact on firm's market value. Black (1976) described the firm's decision on the proportion of profits to distribute to shareholders or to retain within the firm as the "dividend puzzle". Lee (1996) and Kanas (2003) reported that dividends and stock prices are co-integrated.

As a result, the dividend relevancy theories arises and argued that, for example; the MM framework does not consider the tax effects – if different stockholders face different taxation rates on dividends, their preferences would vary accordingly (Allen et al. 2000; Coates et al. 1998), the transaction costs involved when shareholders trade shares to re-invest dividends or to extract more cash, or conflicts of interest which may imply that shareholders would prefer higher dividend payments to reduce the amount of funds controlled by management (Dempsey & Laber 1992; Jensen et al. 1992). Therefore, prominent dividend relevant theories opine for positive and negative relationship based upon the market and firms' conditions.

Clientele Theory

Clientele effect theory notes that investors have different tax, transactions and earnings preferences, where some investors or firms may require cash earnings from dividend payout and others requires capital gain. To illustrate, mature firms usually attract investors with cash dividend or lower tax bracket; whereas, growing firms attract investors with capital gain or investors with higher tax bracket. Thus, the clientele effect dictates the company to choose a specific dividend policy to meet the needs of its investors and their expectation on the recorded dividend policy.

"Bird in Hand" Theory

Market participants may prefer higher dividend payments as opposed to expected future capital gains despite higher tax rate, given that the latter are always prone to uncertainty whereas a cash payment is a more certain as the saying "A bird in hand is worth more than two in the bush." (Fisher, 1961; Lintner, 1962).

Agency Theory

Agency cost arises when management of the firm work for their own agenda such as investing in unprofitable projects that will be associated with high employee compensation and bonuses and negate the fiduciary duty of shareholders' wealth maximization; consequently, the firms with free cash flow are required by the shareholders to pay dividends while management and bondholders may not want to.

Signaling Theory

Lintner (1956) and Lipson et al. (1998) argued that only when managers believe that earnings have increased permanently, they would increase dividends conveying a signal about the positive future. Since number of studies have confirm that there is an asymmetry of information between managers and shareholders. Dividend announcement can be used as signal to market about the firm's brighter future and expected cash flows in near time from the management. In support to Miller and Rock (1985), Bhattacharya (1979) described that many dividend announcements communicate information about good financial future. The information then reflects in stock prices after the announcement. However, during economic downturn or negative net income, managers hesitate to announce cuts in dividend payout to retain the stock price stability. Thus, dividend policy is affected by the past and future expectation of recurring dividend payout.

Ap Gwilym et al. (2005) found that higher payout ratios lead to higher real earnings growth, and not to higher real dividend growth by looking at eleven international markets. Robertson and Wright (2006) studied the US stock markets and found that dividend yields offer a robust predictive power which may be used when forecasting returns. Jiraporn et al. (2016) concluded that more talented executives have a higher tendency to pay dividends showing that they are more confident in their ongoing abilities to generate positive return.

Ownership Structure and Subsidiary Factors

The relationship between dividend policies and volatility may depend on the ownership structure of the firm; for example, owners may be more prone to herding behavior than others. The study of bank dividend policy by Lepetit et al. (2017), reported that when ownership structure is more concentrated, banks tend to pay lower dividends, which may due to opportunistic behavior of asymmetric information. However, Jankensgard and Vilhelmsson (2018) show that the larger number of shareholder base in Swedish firms, has no effect on lowering the stock volatility.

The market reaction to dividend policy may also depend on the past years' dividends payout or it is the first dividend payout by the firm (Desai and Nguyen, 2015; Yu and Webb, 2017) or response to changes in dividend payment patterns, when the changes were not in line with recent market trends and/or when they took place in volatile times (Scott Docking and Koch, 2005). Moreover, the information content of dividend policy may partly depend on subsidiary factors such as reporting standards such as in the Chinese markets (Dedman et al. 2015).

Prior Empirical Evidences

Prior studies investigated more the connections between dividend policies and stock volatility, started with the hallmark evidence by Baskin (1989) and followed by abundant empirical testing; for instance, Naziretal. (2010), Hussainey et al. (2011), Hashemijoo et al. (2012), Profilet and Bacon (2013), Ramadan (2013) Lashgari and Ahmadi (2014), and Shah and Noreen (2016). These studies suggested that share price volatility is negatively related to both dividends yields and the dividend payout ratios in both developed and developing markets such as Pakistan, Iran, Jordan, Malaysia, the U.S., etc. The significance of the relationship varied between studies, which may be due to different samples and periods.

In contrast, examples of results of positive relationship includes Chen et al. (2009), who found positive relationship between cash dividends and stock price in China. Suleman et al. (2011) investigate using data from the Karachi Stock Exchange, showed a significant positive relationship between share price volatility and dividend yield. Gunarathne et al. (2016) and Jahfer and Mulafara (2016) also reported a positive relationship in case of the Sri Lankan and Colombo stock market respectively.

Gunasekarage and Power (2006) provide empirical evidence that the impact of dividend announcements on share prices may be of an uncertain nature. In the case of Nigerian Stock Exchange data, Ilaboya and Omoye (2012) did not find any significant relationships between dividend policies and share price volatility. Camilleri et al. (2018) found different inferences of relationship between dividends policy and stock policy for Mediterranean banks' stock when applied different robustness check with elimination of outliners and setting up of sub-samples.

Henceforth, the dividend policy literature is widespread and expanding, but it still offers unsettled results regarding the effect of dividend policy and stock volatility both in developed and developing market. Moreover, the prior studies have not applied dynamic technique, which could be more appropriate for the study due to the dynamic characteristic of stock market and relevancy of previous dividend policy to investor expectations as purpose in signaling and clientele theories.

Islamic Stocks Investment

Islamic finance industry has been growing rapidly with more than 10 percent growth rate annually. Islamic investment has become an alternative investment class for both Muslim and non-Muslim investors for its distinctive ethical features. Islamic principles provide basis for ethical value in commerce and business operation based on Islamic values of achieving social justice and just risk and return sharing. As a result, stocks that met Islamic principles should have ethical business practices, social responsibility and fiscal conservatism on interest-baring loan.

Therefore, Islamic stocks require examination of Shariah (Islamic law) screening, which modern Islamic scholars and jurists outline general rules for Islamic investors to evaluate or screen whether a particular company is lawful (halal) or unlawful (haram) for investment (Derigs & Marzban, 2008; Wilson, 2004). Consequently, several Shariah or Islamic screening criteria has been created in major stock exchange market such as Dow Jone Islamic Market Index, FTSE Shariah Indexes, and FTSE Bursa Malaysia Shariah Indexes. The screenings are based on two aspects, which are qualitative element and quantitative element. The qualitative screening focuses on lawfulness of the core business activity of a company, whereas the quantitative screening applied a principle of tolerance associated with filtering criteria as follow:

- Debt outstanding ratio: If a company's debt financing is more than 33 percent of its capital, total asset, or market capitalization, then it is impermissible for investment.
- Interest-baring income: If interest-baring income of a company is more than 10 percent of its total income, then it is not permissible for investment.
- Monetary assets: If the composition of account receivables and liquid assets (cash holding and marketable securities) to total assets exceed the threshold, which allow an acceptable ratio of non-liquid assets to total assets at the minimum of 51 percent or a few screenings cite at 33 percent.

Previous research argue that Islamic stock indices provide better long-term diversification benefits compared with their conventional counterparts due to the limit of interest-based leverage would lead to lower systemic risks of Islamic stocks indices, both during expansion and recession Moreover, lower leverage limit may lead the performance of individual firms to be less influenced by interest rate movement and would not fluctuate as much in the light volatile loanable fund market. Empirical evidence suggests there is a lower correlation of individual stock price with other assets as well as the whole market (Iqbal et al., 2010, Dewandaru et al. 2014; Saiti et al. 2016; Al-Khazali et al. 2014; Jawadi et al. 2014)

On the other hand, it is contended that ethical investing could under-perform over the long-term holding period owing to the ethical investment portfolios are subgroups of the market portfolio, and could limit the potential diversification benefits (Bauer, Otten, & Rad, 2006). Conventional stock indices may also outperform Islamic stock indices since the screening requirements might added additional screening and monitoring costs, accessibility of a smaller investment universe, and limited potential for diversification. Some study also argue against potential diversification benefit of Islamic stock since there is a potent causality linear and nonlinear causality between the Islamic and conventional stock markets and between the Islamic stock market and financial and risk factors (Hammoudeh et al. 2014; Ajmi et al. 2014).

Notwithstanding both arguments, many investors are interested in Islamic equity due to various other benefits such as transparency and greater stability of returns; nonetheless, the benefits of dividend have not yet been explored extensively. Due to the screening process, it is expected that Islamic stocks to have low leverage and could representing "value" stock class, which could have more persistent dividend policy. Thus, the behavior of dividend policy and price volatility over time could give insight on the topic of the stability of returns of Islamic stocks.

3. Methodology

Variables

Following the literature in the field (e.g. Baskin, 1989; Hussainey et al. (2011), Shah and Noreen, 2016; Camilleri et al. 2018), the variables included in the models are as follow:

Stock price volatility is modeled after Baskin (1989) as shown in Equation 1 below:

Equation (1): $$SPV_{i,t} = \sqrt{\frac{PH_{i,t}-PL_{i,t}}{\left(\frac{PH_{i,t}-PL_{i,t}}{2}\right)^2}}$$

Where $SPV_{i,t}$ is the stock price volatility for stock i during year t, while $PH_{i,t}$and $PL_{i,t}$ are the highest and lowest prices for stock i during year t, respectively. The $SPV_{i,t}$ variable is used as the dependent variable to test the effect of the dividend yield (DY) and dividend payout ratio (DP). Thus, DP and DY are used as the independent focus variables, where DY is annual percentage of dividend yield on each stock. It is calculated as dividend per common share as a percentage of market value of the common share at the beginning of the year. DP is the percentage of earnings that is paid out to shareholders as dividends annually by calculating dividend per share as a percentage of net income. The DP percentage is confined to a particular year's earnings and dividends. The expected relationship for both DY and DP to SPV are negative according to dividend relevant theories and its prior literatures, or otherwise weak/inverse relationship or null according to MM and EMH frameworks. The hypotheses for the dividend policy variables are as follows:

- H0: There is no significant relationship between DY and SPV.
- H1: There is significant relationship (positive/negative) between DY and stock price volatility.
- H0: There is no significant relationship between DP and SPV.
- H1: There is significant relationship (positive/negative) between DP and SPV

In addition, according to Hussainey et al. (2011) and Shah and Noreen (2016), five control variables are deployed in the testing models due to their infringement on the focus variables of DY and DP, which could result in biased coefficient of DY and DP. The five variables are size (S), earning volatility (EV), asset growth (G), leverage of long-term debt, and earning per share (EPS).

The firms' size expected to be negatively related to SPV since larger firm tend to be more diversified, have more information available, and more arbitrage opportunities in trading resulted in less volatility. Earning volatility and leverage of long-term debt are expected to be positively related to SPV to expected higher risks of the firms. EPS is expected to be positively relationship based on expectation of profitable future as to rate of return effect. Asset growth is included as proxy for growth and investment opportunities to capture for the duration effect.

Therefore, the control variables were setup as follows:

1. S was taken as the total asset or size of firms during in each year expressed as a transformation using the natural logarithm. Total asset allows for measurement of size without the effect of leverage compare to market capitalization.
2. EV in each year was expressed as the standard deviation of the total quarterly earnings before interest and taxes (EBIT) to total assets of that year.
3. G was expressed as the percentage change in total assets at the end of each year, to the level of total assets in the earlier year.
4. LEV is calculated as the ratio of the long-term liabilities over total assets for the firm of each year.
5. EPS is representing a standard measure of earning per share.

Statistical Models

Generalized Method of Moments (GMM) Models

Literatures on dividend policy and stock volatility mostly employed static pooled ordinary least square (POLS), fixed and random effects models (e.g. Hussainey et al. 2011, Shah and Noreen, 2016; Camilleri et al. 2018). However, theoretical debates of dividend relevant theories concur that stock price volatility and dividend policy may have dynamic effect in shaping investors' decision such as signaling, and clientele effect based on prior price volatility and dividend policies. Additionally, endogeneity, unobserved heterogeneity, and correlation between regressors and lag-dependent variable make dynamic fixed or random effects not suitable for the estimation. Pooled Mean Group, Mean Group, Dynamic OLS, and Full-modified OLS models are also not suitable for stock price volatility and dividend policy data, which have relatively large cross-sectional characteristics compare to number of time frequencies; thus, a dynamic panel bias may still exist in these techniques.

Due to the mentioned limitations, the study instead employs the use of both two-step "differenced" and "system" GMM models to test relationship between stock volatility and dividend policy for both conventional and Islamic stocks samples. We also apply lagged variable of DY and DP, to test the relevancy of past dividend policy. Arellano & Bond (1991) develop the dynamic GMM model by differencing all regressors and employing GMM (Hansen 1982). The models for differenced GMM and difference GMM with lagged of DY and DP are as follows:

$$\Delta SPV_{i,t} = \alpha_i + \beta_i \Delta SPV_{i,t-1} + \gamma_{i,t} \Delta DY_{i,t-1} + \delta_{i,t} \Delta DP_{i,t-1} + \theta_{i,t} \Delta X_{i,t} + \Delta \omega_i + \Delta \mu_t + \Delta \varepsilon_{i,t} \quad (1)$$

$$\Delta SPV_{i,t} = \alpha_i + \beta_i \Delta SPV_{i,t-1} + \beta_{i,t} \Delta DY_{i,t-1} + \gamma_{i,t} L.\Delta DY_{i,t-1} + \delta_{i,t} \Delta DP_{i,t-1} + \vartheta_{i,t} L.\Delta DP_{i,t-1} + \theta_{i,t} \Delta X_{i,t} + \Delta \omega_i + \Delta \mu_t + \Delta \varepsilon_{i,t} \quad (2)$$

Where

$SPV_{i,t}$	=	Stock's volatility of firm i in year t
$DY_{i,t}$	=	Dividend yield of firm i in year t
$L.DY_{i,t}$	=	Lag of Dividend yield of firm i in year t
$DP_{i,t}$	=	Dividend payout ratio of firm i in year t
$L.DP_{i,t}$	=	Lag of Dividend payout ratio of firm i in year t
$X_{i,t}$	=	Vector of control variables of firm i in year t
ω_i	=	Cross-sectional or firm-specific effect
μ_t	=	Period-specific effect
$\varepsilon_{i,t}$	=	Error term

A difference GMM model requires the use of lags of dependent and independent variables as "instrument" variables to tackle the problem of correlation between the lagged dependent variable and the error term. However, these instruments may be weak instruments for the differenced variables which cannot be addressed in difference estimator; thus, first difference GMM estimator behave poorly and lead to large sample biases when the independent variables are persistent over time (Blundell & Bond 1998). By using instrument variables, the absence of information about the focus variables in the level form can result in loss of a substantial part of total variance in the data (Arellano & Bover 1995). A difference GMM model also has weakness of magnifying gaps in the case of unbalanced data (Roodman 2009b).

Therefore, a system GMM model (Arellano & Bover 1995; Blundell & Bond 1998) is applied in addition to equation (1) as superior panel dynamic testing. The model combines in a system with the regression in first differences and with the regression in levels, where variables in differences are instrumented with the lags of their own levels, while variables in levels are instrumented with the lags of their own differences (Bond et al. 2001). As a result, the first differenced moment conditions in a difference GMM model are augmented by level moment conditions in a system GMM model for more efficiency in estimation (Blundell and Bond, 1998). Albeit the levels of the explanatory variables are essentially correlated with the country specific fixed effect, those of the differences are not correlated. Furthermore, time dummies and cross-sectional unit dummies may be included to control for the time-specific and unit effects respectively.

The two underlying problems of a system GMM model are the estimations of the standard errors that tend to be critically downward biased and too many instruments problem against cross-sectional units, which can over fit endogenous variables and fail to wipe out their endogenous components, resulting in biased coefficients (Roodman 2009a; Roodman 2009b). Hansen and difference-in-Hansen tests can be weak in the presence of overidentification .Therefore, the first problem can be solved by using the finite-sample correction to the two-step covariance matrix developed by (Windmeijer 2005), while the second problem can be solve by the 'collapse' sub option for the xtabond2 command in STATA or lag limits, which force the use of only certain lags instead of all available lags as instruments. Both empirical choices can be utilized as methods for the reduction of the number of instruments and their linearity in T (Vieira et al., 2013). The study used the first approach and also follow up with post estimation specification tests, namely the Hansen J-test test for over-identifying restrictions after applying Windmeijer correction to correct the distortion of standard deviation, and the Arellano and Bond (1991) test, AR (2), for no autocorrelation in the second-differenced errors.

Quantile Regression

The finding based on GMM models may not be applicable to the whole sample in general or that the finding should be difference across stocks; thus, a robustness check can be applied based on the stock price volatility of sub-groups of classes of stocks. Camilleri et al. 2018 classified the sample in their study into two group using two-step cluster categorizing and then regressive individually using OLS. However, the nature of the data in this study consist of all stocks across industries in a particular index; thus, clustering analysis may not appropriate due to larger cross-sectional units, impeding of industry specific effect, and outliers forming heavy tailed distribution.

Instead, we applied quantile regressions, which the results are more robust than OLS, since quantile regressions are able to describe the entire conditional distribution of the dependent variable without removing outliners by calculating coefficient estimates at various quantiles of the conditional distribution by using quantile regression equation (Coad & Rao 2006). Moreover, variables regressed using a quantile regression can avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Due to the relaxation of this assumption, the study can document, to some extent, firms' heterogeneity and consider the opportunity that estimated slope parameters diverge at different quantiles of the conditional distribution of lower and higher stock price volatility.

Quantile regression (Koenker & Bassett Jr 1978) is used to transform a conditional distribution function into a conditional quantile function by slicing it into segments. These segments describe the cumulative distribution of a conditional-dependent variable Y_i given the explanatory variable X_i with the use of quantiles. Assuming that the θ^{th} quantile of the conditional distribution of the explained variable is linear in x where Quant X_i, the conditional QR model can be expressed as follows:

$$Y_i = X_i'.\beta_\theta + \varepsilon\theta_i$$

$$Quant_\theta(Y_i|X_i) = \inf\{Y: F_i(Y|X)\theta\} = X_i'.\beta_\theta$$

$$Quant(\varepsilon\theta_i|X_i) = 0$$

where $Quant_\theta(Y_i|X_i)$ represents the θ the conditional quantile of Y_i on the regressor vector X_i; β_θ is the unknown vector of parameters to be estimated for different values of θ in (0,1); $\varepsilon_{\theta i}$ is the error term assumed to be continuously differentiable c.d.f. (cumulative density function) of $F_i(Y|X)\theta$ and a density function $F_i(Y|X)\theta$.The value $F_i(Y|X)\theta$ denotes the conditional distribution of Y conditional on X. Varying the value of u from 0 to 1 reveals the entire distribution of Y conditional on X. Thus, the quantile equation for stock volatility can be written as follow:

$$SPV_{i,t} = X_{i,t}'.\beta_\theta + \varepsilon\theta_{i,t} with Quant_\theta(Y_i|X_i) = X_{i,t}'.\beta_\theta \qquad (2)$$

θ^{th} regression quantile of Y_i on the regressor vector X_i, 0<θ<1, solves the following equation

$$\min \beta \frac{1}{n}\left\{\sum_{i,t:y_{i,t}>x_{i,t}'\beta} \theta\left|y_{i,t} - x_{i,t}'\beta\right| + \sum_{i,t:y_{i,t}>x_{i,t}'\beta} (1-\theta)\left|y_{i,t} - x_{i,t}'\beta\right|\right\} = min\ \beta \frac{1}{n}\sum_{i=1}^{n} \rho_\theta \varepsilon_{\theta i,t}$$

where $\rho_\theta()$, which is known as the "check function", is defined as follow:

$$\rho_\theta(\varepsilon_{\theta i,t}) = \begin{Bmatrix} \theta\varepsilon_{\theta i,t} & if\theta\varepsilon_{\theta i,t} \geq 0 \\ (\theta-1)\varepsilon_{\theta i,t} & if\theta\varepsilon_{\theta i,t} \leq 0 \end{Bmatrix}$$

Thus, equation (2) is solved by linear programing methods, as one increase θ continuously from 0 to 1, one traces the entire conditional distributional distribution of $Y_{i,t}$ conditional on $X_{i,t}$ (Buchinsky 1998). The study examined 10th, 25th, 50th, 75th, and 90th quantiles (θ) of the quantile regression models as follow:

$$Q_\theta(SPV) = \alpha_\theta + \beta_{\theta,1}DY + \beta_{\theta,2}DP + \beta_{\theta,3}S + \beta_{\theta,4}EV + \beta_{\theta,5}G + \beta_{\theta,6}LEV + \beta_{\theta,7}EPS + \varepsilon_{\theta i,t} \quad (3)$$

Data

The first set of data in our study are companies listed in the Dow Jones U.S. Index during the year 2005 to 2017 obtained from Bloomberg database. The data compiled the total number of 2456 companies across 13 years as unbalanced data due to additional or subtraction of companies listed in the index over time. The number of companies in the sample varied from year to year with the maximum of 1615 companies in the year 2005 and the minimum of 1209 companies in the year 2017. The descriptive statistical characteristics of the variables are shown in Table 1 and their correlation matrix is shown in Table 2.

Table 1. Dow Jones U.S. Index, Descriptive Statistics of the Variables

Variable	Mean	Std. Dev.	Min	Max	Observations
SPV	0.5402	0.2171	0.0458	2.9650	N = 15700
DY	0.0644	5.6222	0.0000	697.8261	N = 15407
DP	0.6795	17.9890	-29.3333	2062.5630	N = 14619
S	22.3654	1.5194	17.2721	28.5761	N = 15574
EV	0.3410	9.5427	0.0000	916.5426	N = 13789
LEV	0.2163	0.2198	-0.1491	9.9519	N = 15543
G	0.1270	0.5264	-0.9532	29.1903	N = 14524
EPS	7.5873	253.5615	-1600.0000	14656.3100	N = 15490

As shown in table 2, the preliminary finding of correlation between SPV and DY as an explanatory variable show positive relationship. This relationship is conformed with the prior studies (e.g. Hussainey et al. (2011) and Camilleri et al. (2018)), but it is contradicting to the findings of e.g. Baskin (1989), and Shah and Noreen (2016) who reported significant negative relationships. The second explanatory variable, DP, is also shown to have positive relationship, contradicting the earlier findings of e.g. Baskin (1989), Hussainey et al. (2011), Shah and Noreen (2016) and Camilleri et al. (2018). The possible explanation for positive relationship here could due to the sample in this study, which allow for unbalanced data instead of screening for companies which has consistent dividend payout for all years. All variables appear to free from multicollinearity problem with low correlations; however, DY and DP show no significant relationship with SPV in this stage. Most of the control variables present significant relationship with the main regressor, DY and DP; thus, there could be the problem of endogeneity and unobserved heterogeneity, which can be dealt with using GMM estimators.

Table 2. Dow Jones U.S. Index, Variable Correlation Matrix

	SPV	DY	DP	S	EV	LEV	G	EPS
SPV	1							
DY	0.0095	1						
DP	0.0124	0.0001	1					
S	-0.0029	-0.0075	-0.0017	1				
EV	-0.0143*	-0.0003	-0.0001	0.0018	1			
LEV	0.0414***	0.0051	0.0077	0.0384***	-0.0071	1		
G	-0.0754***	-0.0022	-0.0025	-0.0057	0.0059	-0.0192**	1	
EPS	-0.0225***	-0.0003	-0.0009	0.0672***	0.0031	-0.015*	-0.0003	1

Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively

In the case of Dow Jones Islamic U.S. stocks as the second set of samples, the descriptive statistic is shown in table 3. The Islamic stocks' data is screen from the first set of samples, complying the maximum total number of 589 companies across 13 years as unbalanced data. The correlation matrix of the variables in the Dow Jones Islamic index is presented in table 4. Similar to the overall Dow Jones U.S index, the preliminary finding of correlation between SPV and DY and DP as explanatory variables show positive relationships. All variables are free from multicollinearity problem showing low correlation values; however, DY significant relationship with SPV in this stage. Most of the control variables here also show significant relationships with DY and DP; as a result, there could be the problem of endogeneity and unobserved heterogeneity, which can be dealt with by the GMM methods.

Table 3. Islamic Stocks in Dow Jones U.S. Index, Descriptive Statistics of the Variables

Variable	Mean	Std. Dev.	Min	Max	Observations
SPV	0.4843	0.1741	0.0458	1.5713	N = 5319
DY	0.0121	0.0222	0.0000	0.6195	N = 5255
DP	0.4198	7.7050	-40.0000	534.2368	N = 5201
S	22.0907	1.3760	18.1726	26.6510	N = 5290
EV	0.3761	6.9898	0.0000	329.4219	N = 5173
LEV	0.1838	0.1623	0.0000	2.6158	N = 5283
G	0.1350	0.3866	-0.8397	7.1948	N = 4992
EPS	2.1012	22.6785	-1600.0000	110.5300	N = 5261

Table 4. Islamic Stock in Dow Jones U.S. Index, Variable Correlation Matrix

	SPV	DY	DP	S	EV	LEV	G	EPS
SPV	1.00							
DY	0.1138***	1.00						
DP	0.01	0.0594***	1.00					
S	-0.0384***	0.1703***	0.00	1.00				
EV	-0.02	0.00	0.00	0.02	1.00			
LEV	0.0313**	0.2001***	0.0396***	0.1282***	-0.02	1.00		
G	-0.1065***	-0.1172***	-0.01	-0.03	0.01	0.01	1.00	
EPS	-0.0625***	0.01	0.00	0.0470***	0.00	-0.02	-0.02	1.00

Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively

4. Results and Discussions

We first run the regression based on static models using POLS and Fixed effect models on the Dow Jones U.S. Index as similarly tested by prior studies based on the model specification in equation (1) and (2). The results are shown in table 5. We found that the adjusted R-square for model 2 (with lag of DY and DP) is the highest. However, all four models show similar result in explaining power. All variables are shown to be statistically significant at 5 percent except for DP for model 1 and 2 (using POLS). In model 3 and 4 (using fixed effect models), control variables EV and LEV are insignificant. Lag of DY and DP in model 2 and 4 (using equation (2)) are statistically insignificant. Our explanatory variable DY across all four models are positive related to SPV with the coefficient of less than 0.001. The results here are contradicted to the previous studies such as Baskin (1989), Hussainey et al. (2011), Hashemijoo et al. (2012), and Shah and Noreen (2016). However, the variable DP are significant in all Fixed Effect models showing positive relationship. These results are also contradicted with past studies such as Hussainey et al. (2011) and Shah and Noreen (2016). S (models 1 to 4) and LEV (models 1 and 2) variables show negative relationship in line with Song (2012), Hashemijoo et al. (2012), and Shah and Noreen (2016). EV, G, and EPS (models 1 to 4) show negative relationship contradicting the prior evidences by Hussainey et al. (2011), Hashemijoo et al. (2012), and Shah and Noreen (2016).

In order to check the robustness of the inferences of the 2008 crisis, we then included a dummy variable (FCD) denoting the period of the financial crisis in year 2008 and 2009, when the volatility was noticeably higher during these years. The results are shown in table 6., which closely resemble result in table 5. However, the adjusted R-square is considerably higher and the dummy variable for the crisis is positively significant. The results here confirm robustness check with dummy variable but does not affect our models as in the case of Camilleri et al. (2018). This may due to considerably larger sample across multiple industries rather banking institutions, which are heavily affected by the crisis. Thus, the results from models with crisis dummy will be the focus model for our static model with the Dow Jones U.S. Index.

Table 5. Static Models for Dow Jones U.S. Index

	(1) POLS	(2) POLS.L	(3) FixedE	(4) FixedE.L
DY	0.0003***	0.0003***	0.0002***	0.0002***
	(18.33)	(25.03)	(17.47)	(22.28)
DP	0.0001	0.0001	0.0001**	0.0001**
	(1.34)	(1.30)	(2.80)	(2.80)
S	-0.0114***	-0.0104***	-0.0443***	-0.0391***
	(-8.57)	(-7.15)	(-7.65)	(-6.46)
EV	-0.0005***	-0.0004**	0.0001	0.0001
	(-3.53)	(-3.22)	(0.67)	(0.60)
LEV	0.0766***	0.0802***	0.0051	-0.0019
	(6.38)	(6.05)	(0.24)	(-0.09)
G	-0.0414**	-0.0369**	-0.0234***	-0.0246***
	(-3.24)	(-2.91)	(-7.10)	(-6.99)
EPS	-0.0000***	-0.0000***	-0.0000	-0.0000
	(-7.44)	(-6.80)	(-0.92)	(-0.67)
L.DY		0.2816		0.0364
		(1.67)		(0.89)
L.DP		0.0001		0.0000
		(1.15)		(1.43)
_cons	0.7716***	0.7354***	1.5188***	1.3963***
	(26.07)	(23.17)	(11.93)	(10.49)
Prob > F	0	0	0	0
Adjusted R^2	0.0224	0.0282	0.0252	0.0218
N	12624	11338	12624	11338
No. of Groups			1902	1760

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses, correlated random effects - Hausman test showed p-value of 0, we reject the null hypothesis that Random effect model is appropriate.*

Table 6. Static Models for Dow Jones U.S. Index with Crisis Dummy

	(1) POLS	(2) POLS.L	(3) FixedE	(4) FixedE.L
DY	0.0003***	0.0003***	0.0001***	0.0001***
	(15.58)	(21.07)	(12.93)	(12.39)
DP	0.0001	0.0001	0.0001**	0.0001*
	(1.31)	(1.26)	(2.63)	(2.56)
S	-0.0120***	-0.0112***	-0.0511***	-0.0497***
	(-9.01)	(-7.64)	(-8.79)	(-8.18)
EV	-0.0005***	-0.0004***	0.0001	0.0001
	(-3.68)	(-3.42)	(0.52)	(0.48)
LEV	0.0756***	0.0784***	0.0100	0.0043
	(6.30)	(5.91)	(0.47)	(0.20)
G	-0.0415**	-0.0369**	-0.0231***	-0.0233***

	(-3.26)	(-2.93)	(-7.40)	(-7.09)
EPS	-0.0000***	-0.0000***	-0.0000	-0.0000
	(-7.61)	(-6.94)	(-0.99)	(-0.74)
FCD	-0.0613***	-0.0566***	-0.0782***	-0.0775***
	(-11.61)	(-10.53)	(-19.59)	(-18.45)
L.DY		0.2963		0.0583
		(1.72)		(1.21)
L.DP		0.0001		0.0000
		(1.08)		(0.72)
_cons	0.7906***	0.7587***	1.6760***	1.6398***
	(26.71)	(23.78)	(13.12)	(12.26)
Prob > F	0	0	0	0
Adjusted R^2	0.0299	0.0355	0.0587	0.0578
N	12624	11338	12624	11338
No. of Groups			1902	1760

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses, correlated random effects - Hausman test showed p-value of o, we reject the null hypothesis that Random effect model is appropriate.*

As documented by prior studies, static models based on POLS, Fixed Effect, and Random Effect estimators suffer from the problems of endogeneity, unobserved heterogeneity, and correlation between regressors and lag-dependent variable. In order to obtain meaningful results using these models, past studies opted to drop some control variables, which may dilute the theoretical framework of stock price volatility. Moreover, static models failed to capture the dynamic quality of stock market behavior when applying panel data. Therefore, we instead applied dynamic two-step GMM estimators to overcome such problems, we then applied both two-step difference and system GMM models.

Table 7 and 8 present the results from central models for stock price volatility using difference and system GMM estimators from the equations (1) and (2) respectively. The models in table 8 included an extra financial crisis dummy variable. In both tables, we treat all variables as exogeneous with the exception of EV, which is expected to highly correlated or have direct impact on SPV. We also limit the instruments of the explanatory variables, to minimize the overidentification problem. Diagnostic statistics at the bottom indicate the accuracy of the models. All of our models in both tables fail to reject the null of autocorrelation test of order 2, their residuals are free from autocorrelation problem. All of our models are also free from the problem of overidentification (fail to reject the null) as seen that the p-value of Sargan and Hansen tests are more than 5 percent except for model 5 in table 8, where the Sargant test p-value is 0.304, but the Hansen Test p-value is 0.49. The difference-in-Hansen test statistics shows the p-values of more than 5 percent (fail to reject the null); thus, our specifications of instruments used are validated in all models. The coefficients of the autoregressive variable (L.SPV) are less than 0.8, which indicate that the system GMM models may not be superior than difference GMM models. However, the nature of our data is highly unbalanced and having high number of groups or cross-sectional units, therefore, we opted for the result in system GMM models instead of difference GMM models. Nonetheless, the results of difference GMM in model 5 and 6 in both tables are given for comparison.

Turning to our key explanatory variables in models 6 and 8 for both tables 7 and 8, we found that both DY and DP are significant at 5 percent. The coefficients of both dividend variables show very weakly positive relationship with SPV similar to the results obtain by static models; thus, the results here are contradict with current study's prior expected signs but agree with prior studies that show mixed results such as Camilleri et al. (2018). In term of the control variables, LEV, G, and EPS are significant at 5 percent; whereas, EV and S are significant at 10 percent across models 6 and 8 for table 7 and insignificant for table 8. Only variable S in table 7 is in line with prior studies by Song (2012), Hashemijoo et al. (2012), and Shah and Noreen (2016); whereas, other control variables show opposite sign to expectation of previous studies. The lag of DY and DP are not significant in models 8 of both tables. The autoregressive variable or lag of SPV show significant at 1 percent, supporting the use of dynamic model. Lastly, the financial crisis duumy variables are insignificant across in models 6 and 8 in table 8.

Table 7. Dynamic Models for Dow Jones U.S. Index

	(5) D.GMM	**(6) S.GMM**	**(7) D.GMM.L**	**(8) S.GMM.L**
DY	-0.0329	0.0003***	-0.0047	0.0003***
	(-1.26)	(24.28)	(-0.20)	(22.96)
DP	0.0001	0.0001**	0.0001	0.0001**
	(1.27)	(2.66)	(1.18)	(2.76)
S	0.0037	-0.0051**	0.0043	-0.0054**
	(0.30)	(-2.78)	(0.34)	(-3.16)
EV	0.0213*	-0.0002*	0.0180*	-0.0001*
	(2.19)	(-2.45)	(2.21)	(-2.18)
LEV	-0.0162	0.0466**	0.0216	0.0415**
	(-0.42)	(3.17)	(0.42)	(3.04)
G	-0.0096*	-0.0185***	-0.0102*	-0.0164***
	(-2.26)	(-5.24)	(-2.28)	(-5.22)
EPS	-0.0000**	-0.0000***	-0.0000**	-0.0000***

	(-2.88)	(-4.49)	(-2.93)	(-4.44)
L.DY			0.1019	0.0947
			(1.61)	(1.01)
L.DP			-0.0000	-0.0000
			(-1.09)	(-1.07)
L.SPV	0.5101***	0.4224***	0.5763***	0.4842***
	(5.53)	(15.66)	(5.56)	(30.52)
_cons		0.4047***		0.3764***
		(9.03)		(9.79)
Prob > F	0	0	0	0
N	9638	11549	9468	11338
No. of Groups/cross-section	1537	1788	1504	1760
No. of Instruments	12	13	14	13
Arellano-Bond AR (1)	0	0	0	0
Arellano-Bond AR (2)	0.603	0.699	0.223	0.227
Sargan Test of overid. restrictions (p-value)	0.496	0.099	0.201	0.352
Hansen Test of overid. restrictions (p-value)	0.223	0.188	0.252	0.126
Diff. Hansen tests of exogeneity (p-value)	0.223	0.09	0.252	0.094

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses*

Table 8. Dynamic Models for Dow Jones U.S. Index with Crisis Dummy

	(5) D.GMM	(6) S.GMM	(7) D.GMM.L	(8) S.GMM.L
DY	-0.0442	0.0004***	-0.0191	0.0004***
	(-1.39)	(6.40)	(-1.07)	(6.86)
DP	0.0001	0.0001**	0.0001	0.0001**
	(1.18)	(3.13)	(1.80)	(3.08)
S	-0.0008	-0.0023	0.0015	-0.0029
	(-0.08)	(-0.97)	(0.13)	(-1.40)
EV	0.0195***	-0.0000	0.0209***	-0.0000
	(3.55)	(-0.27)	(3.77)	(-0.41)
LEV	-0.0257	0.0374**	0.0016	0.0388**
	(-0.82)	(2.75)	(0.05)	(2.95)
G	-0.0116**	-0.0157***	-0.0109**	-0.0150***
	(-3.12)	(-4.13)	(-2.58)	(-4.40)
EPS	-0.0000**	-0.0000***	-0.0000**	-0.0000***
	(-2.90)	(-4.14)	(-2.85)	(-4.53)

FCD	-0.0816***	0.1384	-0.0671**	0.1423
	(-4.37)	(1.69)	(-2.92)	(1.88)
L.DY			0.1030	0.0653
			(1.44)	(0.80)
L.DP			-0.0000	-0.0000
			(-0.67)	(-0.12)
L.SPV	0.3494***	0.5284***	0.4675***	0.5133***
	(3.91)	(7.89)	(4.59)	(23.69)
_cons		0.2721**		0.2930***
		(3.11)		(5.03)
Prob > F	0	0	0	0
N	9638	11549	9468	11338
No. of Groups	1537	1788	1504	1760
No. of Instruments	16	13	18	13
Arellano-Bond AR (1)	0	0	0	0
Arellano-Bond AR (2)	0.477	0.368	0.868	0.432
Sargan Test of overid. restrictions (p-value)	0.304	0.196	0.479	0.68
Hansen Test of overid. restrictions (p-value)	0.049	0.418	0.449	0.625
Diff. Hansen tests of exogeneity (p-value)	0.94	0.42	0.844	0.625

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses*

We now turn to the regression based on the Islamic stocks in Dow Jones U.S. Index. We also first run static regression using POLS and Fixed effect estimators based on equation (1) and (2). The results are shown in table 9 and table 10 (with the financial crisis dummy variable). We also found that the models with the dummy in table 10 have considerably higher adjusted R-square but all dummy **variables are negatively significant** opposite to that of the Dow Jones U.S. Index sample. The model 3 in table 10 has the highest adjusted R-square of 0.0888. In contrast to the Dow Jones U.S. Index, **DY in Islamic stocks sample is not significant at 5 percent, but DP became significant** at 1 percent and shows negative relationship to SPV across all models with the coefficient of less than 0.001. Despite weak coefficients, these results are consistent with Hussainey et al. (2011) and Shah and Noreen (2016). Our control variables in table 10, S, EV, and G are shown to be significant in POLS models (models 1 and 2) with all negative relationship. Only variable S is in line with prior studies by Song (2012), Hashemijoo et al. (2012), and Shah and Noreen (2016). The lag of DY is also shown to be positively significant. However, EV became insignificant in the Fixed Effect models (model 3 and 4), but EPS become positively significant in model 4 at 10 percent contradicting the prior studies.

Table 9. Static Models for Islamic Stocks in Dow Jones U.S. Index

	(1) POLS	(2) POLS.L	(3) FixedE	(4) FixedE.L
DY	0.8742***	0.3498*	0.1658	-0.0323

	(5.00)	(2.23)	(1.24)	(-0.29)
DP	-0.0001	-0.0001	-0.0002***	-0.0002***
	(-0.62)	(-1.01)	(-3.88)	(-3.31)
S	-0.0106***	-0.0111***	-0.0624***	-0.0546***
	(-5.46)	(-5.77)	(-7.77)	(-6.96)
EV	-0.0003***	-0.0003***	0.0002	0.0002
	(-3.67)	(-3.69)	(1.05)	(0.94)
LEV	0.0083	0.0040	0.0090	-0.0050
	(0.44)	(0.21)	(0.34)	(-0.18)
G	-0.0549***	-0.0545***	-0.0148*	-0.0172**
	(-6.83)	(-6.43)	(-2.29)	(-2.85)
EPS	-0.0005	-0.0004	0.0002*	0.0002**
	(-1.08)	(-1.09)	(2.14)	(3.16)
L.DY		1.0771***		0.5623**
		(5.12)		(3.17)
L.DP		-0.0000		-0.0001
		(-0.11)		(-0.86)
_cons	0.7174***	0.7179***	1.8675***	1.6908***
	(17.02)	(17.04)	(10.57)	(9.78)
Prob > F	0	0	0	0
Adjusted R^2	0.0371	0.0518	0.053	0.0502
N	4834	4479	4834	4479
No. of Groups			561	547

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses, correlated random effects - Hausman test showed p-value of 0, we reject the null hypothesis that Random effect model is appropriate.*

Table 10. Static Models for Islamic Stocks in Dow Jones U.S. Index with Crisis Dummy

	(1) POLS	(2) POLS.L	(3) FixedE	(4) FixedE.L
DY	0.9307***	0.4044*	0.2789*	0.0786
	(5.26)	(2.51)	(2.25)	(0.77)
DP	-0.0001	-0.0002	-0.0002***	-0.0002***
	(-0.99)	(-1.41)	(-3.59)	(-3.34)
S	-0.0112***	-0.0117***	-0.0732***	-0.0695***
	(-5.76)	(-6.09)	(-8.91)	(-8.51)
EV	-0.0004***	-0.0003***	0.0002	0.0001
	(-3.87)	(-3.90)	(0.95)	(0.78)
LEV	0.0063	0.0017	0.0081	-0.0044
	(0.34)	(0.09)	(0.30)	(-0.16)
G	-0.0556***	-0.0550***	-0.0132*	-0.0146*
	(-6.78)	(-6.36)	(-2.13)	(-2.51)
EPS	-0.0005	-0.0004	0.0002	0.0002*
	(-1.07)	(-1.09)	(1.75)	(2.49)
FCD	-0.0421***	-0.0384***	-0.0634***	-0.0621***

	(-6.33)	(-5.74)	(-13.70)	(-13.03)
L.DY		1.0816***		0.5868***
		(5.26)		(3.98)
L.DP		-0.0000		-0.0001
		(-0.36)		(-1.60)
_cons	0.7358***	0.7359***	2.1147***	2.0275***
	(17.43)	(17.49)	(11.69)	(11.26)
Prob > F	0	0	0	0
Adjusted R^2	0.0438	0.0577	0.0888	0.0874
N	4834	4479	4834	4479
No. of Groups			561.0000	547.0000

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses, correlated random effects - Hausman test showed p-value of 0, we reject the null hypothesis that Random effect model is appropriate.*

Regardless of the results in tables 9 and 10, the result obtained through dynamic GMM models in tables 11 and 12 should provide more consistent and efficient explanations due to the limitation of static models. As in the case of the Dow Jones U.S. Index, we still treat all variables as exogeneous with the exception of EV and limit the instruments of the explanatory variables, to minimize the overidentification problem. The diagnostic statistics in tables 11 and 12 for all models show that there is no problem of autocorrelation of order 2 and overidentification. Moreover, the specification of instrument used are validated based on the difference-in-Hansen test statistics, showing the p-values of more than 5 percent. Similarly, we opted for the result system GMM models rather than difference GMM models due to the nature of our data, despite the autoregressive coefficients of less than 0.8 in most models.

Upon examining the dividend variables, we found that both DY and DP are not significant in all models from both tables. In table 11, only control variable G in model 8 is significant at 5 percent. In table 12 after controlling for the crisis period, the variable G are significant for models 6 and 8 at 5 percent and the variable lag of DY is significant at 5 percent. The crisis dummies also turn out to be insignificant in all models. The autoregressive variable LSPV are only significant in model 6 and 8 for both tables. The result here are in line with recent studies by Shah and Noreen (2016) and Camilleri et al. (2018) initially, before dropping some control variables. However, the result here could be affected by the present of outliners; therefore, robustness checks are made using quantile regressions, which show the effect of the explanatory variables at different quantile of SPV.

Table 11. Dynamic Models for Islamic Stocks in Dow Jones U.S. Index

	(5) D.GMM	(6) S.GMM	(7) D.GMM.L	(8) S.GMM.L
DY	0.6953	0.1521	-0.6623	-2.0637

	(0.40)	(0.11)	(-0.23)	(-1.45)
DP	0.0382	-0.0016	0.0674	0.0262
	(1.59)	(-0.17)	(1.10)	(1.41)
S	0.0086	-0.0003	-0.0433	-0.0000
	(0.17)	(-0.06)	(-0.92)	(-0.01)
EV	0.0191	0.0086	0.0126	0.0055
	(1.81)	(1.43)	(1.21)	(1.74)
LEV	0.0080	-0.0030	0.0272	0.0258
	(0.07)	(-0.12)	(0.10)	(0.43)
G	-0.0075	-0.0126	0.0010	-0.0205**
	(-0.49)	(-1.27)	(0.07)	(-2.62)
EPS	-0.0001	-0.0003	-0.0000	-0.0002
	(-0.54)	(-0.80)	(-0.09)	(-0.86)
L.DY			0.2782	1.0111
			(0.17)	(1.42)
L.DP			-0.0011	-0.0002
			(-0.46)	(-0.70)
L.SPV	0.9272	0.6822***	0.3827	0.6126***
	(1.96)	(4.38)	(0.73)	(4.35)
_cons		0.1493*		0.1806
		(1.98)		(1.60)
Prob > F	0.006	0	0.001	0
N	3949	4542	3895	4479
No. of Groups	511	553	509	547
No. of Instruments	12	17	14	21
Arellano-Bond AR (1)	0.207	0.939	0.092	0.207
Arellano-Bond AR (2)	0.729	0.178	0.285	0.827
Sargan Test of overid. restrictions (p-value)	0.992	0.42	0.977	0.957
Hansen Test of overid. restrictions (p-value)	0.52	0.11	0.813	0.43
Diff. Hansen tests of exogeneity (p-value)	0.52	0.26	0.813	0.303

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses*

Table 12. Dynamic Models for Islamic Stocks in Dow Jones U.S. Index with Crisis Dummy

	(5) D.GMM	(6) S.GMM	(7) D.GMM.L	(8) S.GMM.L
DY	-1.9651	0.1734	-2.1550	0.1735
	(-1.00)	(0.99)	(-0.76)	(0.98)
DP	0.0375	-0.0000	0.0423	-0.0001
	(1.27)	(-0.70)	(1.92)	(-0.69)
S	-0.0486	-0.0026	-0.0859*	-0.0052
	(-0.73)	(-1.03)	(-2.34)	(-1.72)
EV	0.0125	0.0000	0.0018	-0.0001
	(1.08)	(0.08)	(0.19)	(-0.80)
LEV	0.1247	0.0060	0.2288	0.0061
	(1.78)	(0.40)	(1.44)	(0.36)
G	-0.0057	-0.0177**	0.0096	-0.0192**
	(-0.22)	(-3.09)	(0.49)	(-3.28)
EPS	-0.0001	-0.0001	0.0000	-0.0001
	(-0.56)	(-0.91)	(0.90)	(-0.90)
FCD	0.0106	0.0881	0.0049	0.0543
	(0.31)	(1.78)	(0.21)	(0.70)
L.DY			0.8986	0.5306**

			(0.80)	(2.68)
L.DP			-0.0010	0.0001
			(-0.58)	(0.64)
L.SPV	0.2904	0.5310***	0.0580	0.4451***
	(0.61)	(9.10)	(0.17)	(13.83)
_cons		0.2655***		0.3643***
		(3.35)		(4.47)
Prob > F	0	0	0	0
N	3949	4542	3895	4479
No. of Groups	511	553	509	547.
No. of Instruments	16	13	18	13
Arellano-Bond AR (1)	0.354	0	0.094	0
Arellano-Bond AR (2)	0.516	0.093	0.313	0.212
Sargan Test of overid. restrictions (p-value)	0.999	0.62	0.942	0.547
Hansen Test of overid. Restrictions (p-value)	0.231	0.583	0.572	0.439
Diff. Hansen tests of exogeneity (p-value)	0.589	0.815	0.271	0.439

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in parentheses*

Robustness Analysis

As prior studies such as Camilleri et al. (2018) noted, dividend policy variables may show tendency to be fluid and can be sensitive to the treatment of outliers and sampling procedures. For instant DY or DP may become more significant explanatory than each other or change in directions of relationship of DY and DP to SPV. Consequently, additional regressions are tested to address these issues using simultaneous quantile regressions based on equation (3). The simultaneous quantile regressions show the effect of the explanatory variables at different quantiles of SPV; hence, they give better estimations when there are outliners, which is expected within our sample due to large number of firms. Moreover, the estimations given at different quantiles can also represent classes of stocks such as low SPV stock may refer to more mature, “leaders” , or “value” stocks, while high SPV stocks may refer to more speculative stocks.

Tables 13 and 14 present the results of quantile estimations at 10, 25, 50, 75, and 90 percent quantiles for the Dow Jones U.S. Index stocks without and with crisis dummy respectively. Figures 1 and 2 (appendix) show the effects of each variables for all quantiles within (0, 1) range of SPV. In both tables, we found that both dividend variables are not significant at any percentage points of quantiles. The results here prove the sensitivity to outliners of the study and also show that the weak coefficients (less than 0.001) obtained from system GMM cannot affect the SPV after we control for outliners. Thus, quintile regression strengthens the our suspicious of weak coefficients of the dividend variables. The results for control variables show little difference across quantile except for EPS, which is significant at 75 and 90 percent quantile in both tables. The financial crisis dummy variable become significant similar to those in static models.

Table 13. Quantile Regressions for the Dow Jones U.S. Index

	q10	**q25**	**q50**	**q75**	**q90**
DY	0.00061	0.00050	0.00036	0.00017	-0.00007
	[0.05]	[0.07]	[0.19]	[0.37]	[0.46]
DP	0.00013	0.00010	0.00005	0.00074	0.00367
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
S	-0.01057***	-0.01262***	-0.01123***	-0.00859***	-0.01472***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
EV	0.00008	-0.00002	-0.00022	-0.00062	-0.00080*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LEV	0.05802***	0.04402***	0.04721***	0.07755***	0.13660***
	[0.01]	[0.01]	[0.01]	[0.02]	[0.03]
G	-0.07395***	-0.06618***	-0.06275***	-0.05004***	-0.04822*
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
EPS	0.00000	-0.00000	-0.00001	-0.00002***	-0.00003***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
_cons	0.54597***	0.67253***	0.74183***	0.80643***	1.08546***
	[0.03]	[0.03]	[0.03]	[0.05]	[0.07]

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in brackets, Robustness using bootstrap replications of 1000 standard error*

Table 14. Quantile Regressions for the Dow Jones U.S. Index with Crisis Dummy

	q10	**q25**	**q50**	**q75**	**q90**
DY	0.00061	0.00049	0.00035	0.00016	-0.00009
	[0.05]	[0.09]	[0.20]	[0.39]	[0.46]
DP	0.00013	0.00009	0.00004	0.00069	0.00362
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
S	-0.01095***	-0.01326***	-0.01195***	-0.00981***	-0.01543***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
EV	0.00004	-0.00003	-0.00024	-0.00065	-0.00083
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LEV	0.05638***	0.04812***	0.04679***	0.07112***	0.12982***
	[0.01]	[0.01]	[0.01]	[0.02]	[0.03]
G	-0.07543***	-0.06650***	-0.06200***	-0.05055***	-0.04920**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
EPS	0.00000	-0.00000	-0.00001	-0.00002***	-0.00003***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
FCD	-0.02628***	-0.03341***	-0.05185***	-0.08056***	-0.10993***
	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]
_cons	0.55851***	0.68954***	0.76296***	0.84288***	1.11068***
	[0.03]	[0.03]	[0.03]	[0.05]	[0.07]

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in brackets, Robustness using bootstrap replications of 1000 standard error*

In the case of Islamic stocks in the Dow Jones U.S. Index, the results in tables 15 and 16 and figures 3 and 4 (appendix) display that DY variables are significant at 5 percent across all quantiles in contrast to the insignificant relationships found using system GMM models. Thus, a more restrictive classes of stocks could provide significant relationship similar to prior studies' sample selection, which focus on smaller particular groups of stocks with consistent dividend payout. In table 16, the coefficient of DY is higher in the upper quantile, and lowest in the 10 percent quantiles at 0.87. Thus, DY has a direct affect SPV at around 1 to 1 ratio across all quantiles. Only control variable G show significant relationship across all quantiles consistent with the result from system GMM models. The financial crisis dummy proves to be significant here similar to the result in static models.

Table 15. Quantile Regressions for Islamic Stocks in the Dow Jones U.S. Index

	q10	**q25**	**q50**	**q75**	**q90**
DY	0.74828***	0.89118***	1.09417***	1.02292**	1.18619**
	[0.20]	[0.20]	[0.23]	[0.35]	[0.38]
DP	0.00020	0.00005	-0.00010	-0.00032	0.00055
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
S	-0.00627	-0.00752	-0.00498	-0.00440	-0.00875*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
EV	0.00021	0.00003	-0.00013	-0.00040	-0.00083
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LEV	-0.00617	-0.01032	-0.02945	-0.00752	0.02932
	[0.02]	[0.02]	[0.02]	[0.02]	[0.04]
G	-0.06623***	-0.06349***	-0.05460***	-0.04878***	-0.04536**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
EPS	-0.00215	-0.00502	-0.00892	-0.01186**	-0.01021***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]
_cons	0.44655***	0.55284***	0.59004***	0.68742***	0.90011***
	[0.07]	[0.08]	[0.08]	[0.09]	[0.08]

*Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in brackets, Robustness using bootstrap replications of 1000 standard error*

Table 16. Quantile Regressions for Islamic Stocks in the Dow Jones U.S. Index with Crisis Dummy

	q10	q25	q50	q75	q90
DY	0.87259***	0.93969***	1.14751***	1.23886***	1.04923**
	[0.23]	[0.20]	[0.27]	[0.35]	[0.39]
DP	0.00020	0.00004	-0.00014	-0.00036	0.00052
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
S	-0.00612	-0.00854*	-0.00552	-0.00577	-0.00962*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
EV	-0.00024	0.00001	-0.00027	-0.00043	-0.00084
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
LEV	-0.02153	-0.01622	-0.01178	0.00315	0.04060
	[0.02]	[0.02]	[0.02]	[0.03]	[0.04]
G	-0.06725***	-0.06217***	-0.05459***	-0.05512***	-0.03770*
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
EPS	-0.00225	-0.00511	-0.00922	-0.01157**	-0.01091***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]
FCD	-0.02059**	-0.02157**	-0.04227***	-0.06888***	-0.09242***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
_cons	0.44949***	0.58051***	0.60605***	0.72189***	0.92692***
	[0.07]	[0.08]	[0.09]	[0.08]	[0.09]

Note: *, **, ***Significant at 90, 95, and 99 percent level of confidence respectively, Standard errors are in brackets, Robustness using bootstrap replications of 1000 standard error

Discussion

Majority of past studies suggest that dividend policy variables DY and DP are related to the SPV based on different samples across the globe with mixed results in term of the directions of relationship, while some of the studies show insignificant relationship. The inconclusive results are mainly due to the variation in samples and technique deployed; however, prior studies document the recurring problem of multicollinearity, unobserved heteroskedasticity, and outliners. By using GMM methods and quantile regressions instead of static models, we are able to minimize these problems. Our results offer new insight to the topic by using larger sample in both samples of Islamic stocks and all stocks in the Dow Jones U.S. Index and by using the mentioned techniques instead of reduction of variables. We are able retain the theoretical frameworks and their implication of stock volatility.

Our results confirm that the financial crisis improves the explanatory power in the case of static, difference GMM models, and quantile regressions, but not in the case of system GMM. Thus, dividend policy may constitute minute effect on SPV than anticipated compare to other factor such as trading setup, liquidity factors, macroeconomic factors, and international trade and finance, which can be affected by the crisis (Camilleri et al. 2018).

Moreover, quantile regressions or sample clustering offers new insight about the dividend-SPV relationship and strongly affected the coefficient of the DY and DP. The implication of the changing in coefficients could due to the discrimination from investors in choosing the class of stocks to invest, which can be describe in their volatilities. We also found that the dividend-SPV relationship could react differently for a specific type of stocks such as Islamic stocks compare to overall market. This phenomenon can be explained by the preferences of investors, the gaining interest in ethical stocks, and the choice of portfolio diversification. Our results also show that past dividend policies do not affect the present SPV negating the argument of longer horizon effect of dividend policy.

Turning to the results of the Dow Jones U.S. index, we found that only DY is significant in system GMM models with very weak coefficients and later turn out to be insignificant in quantile regressions in both cases where we include and exclude financial crisis effect. Thus, at both overall market level and each class of stocks, dividend contributes only a minor component to the SPV. The results conform toward with the MM framework and EMH that dividend policy has become less relevant. The implications of the finding are that investors are better inform about the companies they invested as information are easily accessed and timely than before. Moreover, the U.S. market present semi-strong to strong EMH, which also allow investors to formulate different kinds of trading strategies over different horizons. We also found that larger size of a company will have lower volatility, which due to the facts that larger companies are more diversified and have stable earning. In addition, growing company and company that has higher EPS will have less volatility. The contradicting results from prior studies here is due to the nature of companies listed in the Dow Jones U.S. index, which is typically larger and more mature than companies in developing market. It is not necessary that companies here are in growth stage and opted to retain dividend, but the index has a mixed of technology companies, which also categorized by high growth and has tendency to retain more cash. As Fama & French (2001) noted, there is a general tendency for US-listed firms to become less likely to pay dividends in favor of pursuing growth-oriented strategies which require extensive cash resources. Lastly, higher leverage contributes to higher SPV, conforming the with theoretical explanation of stability of companies financing.

In the case of Islamic stocks in the Dow Jones U.S. Index, we did not find a significant relationship between dividend and SPV at market level based on GMM models. The results here agree with MM framework and EMH that dividend policy has become less relevant as that of the overall Dow

Jones U.S. Index. However, we found DY to be positively significant when examined according to the class of stock based on the SPV. The results agree with the static models. The inferences here could be that investors especially specific group of investors who concentrated on lower leverage stocks or "value" stocks and ethical stocks are discriminating in choosing their own class of stocks. Thus, changes in dividend yield such as dividend yield increase could serve as a signaling tool for investors to buy more abruptly in that class of stocks that they are interested in but may be indifferent in other classes of stocks. Hence, these investors could be specific "clients" to each class of stock in the Dow Jones Islamic U.S. index or the lower leverage companies. Moreover, DY affects more for higher volatility stocks compare to lower volatility stocks. The implications here is that companies that has higher volatilities are relatively less mature and less diversified or they could be the "laggard" companies compare to the companies with lower SPV in the same industries. We also found that in both quantile regressions and GMM models, higher asset growth will reduce the volatility. The companies classified in the Dow Jones Islamic U.S. stocks have relative low leverage compare to overall market; hence, asset growth here can be proxy for profitability, better management, and growth-oriented strategies instead of growing companies.

5. Conclusion

The relationship between dividend policy (DY and DP) and stock price volatility remains as a "dividend puzzle" with supporting evidences for both dividend relevance and dividend irrelevance theories. Examining this issue contributes to new insight and implication in corporate finance and has direct implication for management adopting suitable dividend policy. It would help improve investors' judgment on their investment decision. Therefore, the purpose of our study is to shed light on this puzzle by testing both conventional and Islamic equity with the use of relatively advanced GMM methods and quantile regressive models. We investigate the relationship on stocks in the Dow Jones U.S. Index controlling for size, asset growth, leverage ratio, EPS, and earning volatility. We found that both GMM methods and quantile regressions provide deeper insight and complement each other. The 2008-2009 crisis also constitutes better explanation of SPV. However, past year's dividend variables do not affect the present SPV.

We conclude that dividend policy contributes a minor component in the explanation of SPV. In both cases of all stocks and Islamic stocks, dividend variables are not significant or has weak effect on SPV as estimated by GMM models. Thus, the results follow the MM framework and EMH indicating the less relevancy dividend overtime and a general tendency for US-listed firms such as those in the technological sector to become less likely to pay dividends in pursuit of growth instead. The results from quantile regression for all stocks also are in line with the GMM models; whereas, the results from quantile regression for Islamic stocks show significant and strong positive relationship between DY and SPV. This finding could indicate the dynamic of investors preference and firms' dividend policy. We found that investors who invested in Islamic stocks or low leverage stock may have a discriminating tendency in choosing the class of stock according to their preferences but may be indifferent to other classes of stocks. Thus, there could be clientele effect in each class of stock for Islamic stocks.

Our study has three main contributions. First, our evidences contribute to the literature on dividend policy. Second, our study helps both companies and investors to be better informed on stock price reaction on dividend announcement. A recommendation for company can be made that it is less relevant for dividend policy to affect stock prices especially increment or reduction in dividend payout. Another recommendation for investor is that a higher dividend yield could excite the investors as positive signal in Islamic or low leverage/ "value" stocks, to buy more of the same class of stock they invested. Third, we contribute to the literature on the stability and potential diversification of Islamic stocks. Overall, Islamic stocks in the Dow Jones U.S. Index are as stable as non-Islamic stocks, but they also attract specific group of investors according to classes, which relies on dividend yield as positive signal for the future.

The limitation of the study is the data is still highly unbalanced resulting in disagreement between models as in the case of static and dynamic models, and the case of difference and system GMM models. The future research can be extended by exploring new techniques such as non-linear techniques and new proxy to better capture volatility.

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