Shariah stocks as an inflation hedge in Malaysia

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31 May 2016

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Abstract

The purpose of this paper is to study the hedging effectiveness of Shariah (Islamic) stock returns against inflation over the post financial crisis period in Malaysia using wavelet analysis. By using wavelet tools such as wavelet coherence and the wavelet phase angle, the resulting analyses were able to measure cross-correlations and causality between the time series as a function of time-scales. Results tend to indicate that for investment horizons not exceeding 3 years, the FTSE Bursa Malaysia Emas Shariah Index constituent returns can provide hedging against inflation as real returns are largely uncorrelated with inflation.

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1. Introduction

Long since Irving Fisher (1930) had introduced the Fisher hypothesis, numerous empirical studies have been done on the Fisher equation and yet, this equation has found limited empirical support (Jaffe & Mandelker, 1976; Bodie, 1976; Fama & Schwert, 1977; Fama, 1981; Geske & Roll, 1983). According to Fisher hypothesis, the nominal return on an asset is the sum of the constant real rate or return on that asset and the expected inflation rate. This is expressed as

$$E(\tilde{R}_{jt}|\emptyset_{t-1}) = E(\tilde{\imath}_{jt}|\emptyset_{t-1}) + E(\tilde{I}_t|\emptyset_{t-1}),$$

where $\tilde{R}_{jt}$ is the nominal return on asset j from t-1 to t, $E(\tilde{\imath}_{jt}|\emptyset_{t-1})$ is the equilibrium expected real return on the asset implied by the set of information $\emptyset_{t-1}$ available at t-1, $E(\tilde{I}_t|\emptyset_{t-1})$ is the expected value of the inflation rate $\tilde{I}_t$ that can be made on the basis of $\emptyset_{t-1}$, and tildes denote random variables. This equation shows that nominal returns vary point to point with expected inflation and it also assumes that the expected real returns are constant. Further, it implies that the asset is a complete hedge against inflation and that ex post real return on the asset is uncorrelated with the ex post inflation rate (Fama & Schwert, 1977).

As mentioned, limited support has been found for this equation and instead a negative relationship has been found between stock returns and inflation across various countries. One explanation put forth is the Mundell-Tobin effect (a decline in the marginal product of capital due to the real balance response to inflation) which Levi and Makin (1978) and Peek & Wilcox (1983) had demonstrated to have considerable significance.

Another main explanation in academic literature for this negative relationship between stock returns and inflation is the proxy hypothesis offered by Fama (1981). Fama (1981) had argued that the relationship between inflation and stock returns is a proxy for two other relationships: (i) as the growth in real aggregate economic activity is expected to slow down, the growth rate for the demand of real cash balances is also expected to slow down, which leads to an increase in future expected and current inflation (ii) high growth rates of aggregate economic activity are anticipated by high real stock returns. It is the anticipated business fluctuations that drive the negative relations between inflation and stock returns.

Yet another possible explanation was presented by Geske & Roll (1983) which provided monetary and fiscal linkages to the inflation-stock returns relations. Geske and Roll hypothesized that an anticipated decline in real economic activity signals a decline in stock returns, which leads to a reduction in government revenues and hence, an increase in the budget deficit. This leads to a monetization of debt and results in a rise in inflation.

Extending the work of Geske and Roll (1983), Kaul (1986) hypothesized that the relation between stock returns and inflation is caused by an equilibrium process in the monetary sector. A pro-cyclical monetary policy results in a positive relationship between real economic activity and inflation. When combined with a positive relationship between stock returns and anticipated economic activity, it would give rise to a positive co-movement of stock returns and inflation.

In the Malaysian context, using the Kuala Lumpur Stock Exchange (KLSE) Index (1974-1986) to calculate stock returns, Gan (1991) found a negative impact of anticipated inflation on real stock returns. He also found that inflationary shocks constitute an independent source of variation in the real stock returns and observed a positive relationship between inflation and economic activity. These findings indicate that Fama's proxy hypothesis cannot be used to explain the negative relationship between stock returns and inflation. An additional finding was the responsiveness of the real stock returns to monetary innovations suggesting the existence of an additional channel in which monetary policy can impact the real economy.

Ibrahim (2011) found support for the Fisher hypothesis with respect to the Malaysian stock market for the pre-financial crisis period (1988-1996) but not for the post-crisis period and attributes the breakdown in the long-run relationship to the dynamic changes in the inflation process.

Using maximal overlap discrete wavelet transform (MODWT), Kim & In (2005) found that the relationship between inflation and stock returns in the US market is positive in the short horizon, negative for the rest of the wavelet scale and positive at greater than 128-month period. Generally, their results do not support the role of stock returns as an inflation hedge during their sample period.

Using wavelet coherence (WTC) and wavelet phase angle ($\phi_{xy}(u,s)$) over a long sample period from 1961-2012, Tiwari et al. (2015) found positive correlation between inflation and stock returns in Pakistan at the higher time scales when consumer price inflation was used but found them to be independent when producer price inflation was used.

Fisher hypothesized that the real and monetary sectors of the economy are largely independent and so the main purpose of this paper is to uncover any dependence among the variables, the strength of association between variables, as well as the direction of their relationships over time and across different frequencies, if any dependence exists. Unconditional correlations can provide evidence of dependencies among variables but do not provide evidence for how dependencies may develop over time and across different frequencies, nor do they indicate any causality between time series.

Wavelet analysis is a tool for analysing localized variations of power within a time series, allowing for the determination of both the dominant modes of variability as well as how those modes vary in time by decomposing a time series into time-frequency space (Torrence & Compo, 1998). In the context of a study of Fisher hypothesis, a time-frequency decomposition can provide valuable insight into the relationship between inflation and stock returns on a scale-by-scale (or multi-horizon) basis. Although there have been many studies on Fisher hypothesis using traditional econometrics methods, studies using wavelet analysis have been few. There have been instead more studies on the measurement of core inflation and on the relationship of money growth and inflation than on fisher hypothesis using this technique.

This paper focuses on the post-crisis period of 2008 – 2015 for returns on the FTSE Bursa Malaysia Emas Shariah Index. As far as I am aware, there has not been any study on the relationship between stock returns, inflation and real economic activity in the Malaysian context using wavelet analysis nor has there been any study on any Shariah index in this context. It would be useful to investors in the Emas Shariah index to learn about any hedging ability of Shariah stocks on inflation.

The continuous wavelet transform (CWT) is employed in this paper as it is a signal processing tool which can identify local correlation, the relative values of the coherency and local causal relationship between time series in the time domain at different frequencies without having to rely on traditional econometrics methods. Its attractiveness is also in its ability to depict these in one picture. Moreover, CWT is able to deal with nonstationary time series. From two CWT, the Cross Wavelet Transform (XWT) and the Wavelet Coherence (WTC) are constructed. The XWT exposes the common power between time series and their relative phase in time-frequency space. The WTC can be thought of as the local correlation between two CWT. It finds any significant coherence even if the common power is low (Grinsted et al., 2004).

The rest of the paper is organized as follows. Section 2 explains the use of wavelet analysis in economics and finance literature. Section 3 explains the methodology, including an explanation of wavelets, the continuous wavelet transform and its methods. Section 4 describes the results. Section 5 contains the concluding remarks.

2. Wavelet analysis in economics and finance

Wavelet analysis has been extensively applied in engineering and scientific studies such as in the area of geophysics (Torrence & Compo, 1998; Grinsted et al., 2004; Kumar & Foufoula-Georgiou, 1997, Lau & Weng, 1995); in medicine (Salvador et al., 2006; Sahambi et al., 1997, Archaya et al., 2006); in the field of engineering (Lin & Qu, 2000, Hou et al., 2000); in meteorology (Myers et al., 1993; Gupta & Waymire, 1993) and in astronomy and astrophysics (De Moortel et al., 2000; and Zombeck, 2006), among others.

Wavelet analysis has not been as widely applied in social sciences such as finance and economics. Several studies in this area have been on the multi-horizon nature of systematic risk of financial assets (Masih et al., 2010; Gençay et al., 2003) portfolio diversification (Najeeb, Bacha, & Masih, 2015), decomposition of economic relationships (Ramsey & Lampart, 1998), US stock price behavior (Ramsey et al., 1992), the relationship between stock returns and macroeconomic variables (Gallegati M. , 2008), the measurement of business cycles (Yogo, 2008), the relationship between commodities (Vacha & Barunik, 2012) and the introduction to the use of wavelet analysis in econometrics by Goffe (1994) among others.

According to Aguiar-Conraria et al. (2008), prior to the adoption of cross-wavelet tools, wavelet analysis was not as popular as the more traditional time-domain methods because the discrete wavelet transform (one of two classes of wavelet transforms) was used mainly as a lowpass filter (which passes only the low frequencies or long cycles in the data) and a highpass filter (which passes only the high frequencies or annual cycles in the quarterly or monthly data, also known as seasonality). The question of how a researcher could isolate the cyclical component of an economic time series could otherwise be addressed with more traditional band pass-filtering methods, such as the Baxter-King filter (Baxter & King, 1999). The other reason posited is that these techniques have been applied to analyze several time series individually before studying the decompositions using traditional time-domain methods, such as correlation analysis and Granger causality. It was the advent of cross-wavelet tools such as the cross-wavelet power, the cross-wavelet coherency and the phase difference proposed by Hudgins et al. (1993) and Torrence and Compo (1998) which finally allowed for the direct study of the relationship between two time series in the time-frequency domain.

3. Methodology

This section describes the data and provides an overview of the various signal processing tools used in various fields, of the choice between the discrete wavelet transform (DWT), the maximal overlap DWT (MODWT) and the CWT, and finally discusses the wavelet methods, i.e. the cross-wavelet transfor (XWT), the cross wavelet power and the WTC between two CWT.

3.1.Data

All time series are monthly covering the period between 2007 and early 2015 as the FTSE Bursa Malaysia Emas Shariah index data are only available from 2007. All data are sourced from Datastream and expressed in natural logarithm.

Stock returns and inflation rates are computed as their logarithmic first-differences. The proxies for economic activity and future economic activity are the annual growth rates of the Industrial Production Index and its annual growth rates for the period t+1 following Kaul (1987), as a macro model to determine anticipated real activity is beyond the scope of this paper.

The inflation rates are measured from the Consumer Price Index and actual inflation rates are used instead of decomposing it into expected and unexpected components, following Tiwari et al. (2015), Ibrahim (2011), Gultekin (1983) and others. We take note of the concerns of Gan (1991) and McCallum (1976) who pointed out that using actual inflation as a proxy for expected inflation gives rise to errors-in-variable problem. However, this paper does not employ any traditional regression technique so as to be concerned about the issue of a beta coefficient that is biased towards zero.

Nominal stock returns are calculated from the FTSE Bursa Malaysia Emas Shariah index. It is a Shariah-compliant index, meaning that its constituents are screened according to the Malaysian Security Commission’s Shariah Advisory Council (SAC) screening methodology. Nominal stock returns are adjusted for inflation to derive the real stock returns.

Fourier Analysis

A method for analysing relations at different frequencies is the Fourier analysis. It is a technique for transforming our view of a signal from a time-based one to a frequency-based one as it breaks down the signal into constituent sinusoids of different frequencies. However, its drawback is that in transforming a signal to a frequency domain, time information is lost, making it impossible to tell when a particular event took place. If the signal is stationary, then time information would not be so important but if it is nonstationary or contains transitory characteristics such as drifts, trends, abrupt changes or beginnings and ends, then Fourier analysis would not be able to detect them.

A variant of the Fourier analysis, the Short Time Fourier Transform (STFT), corrects this

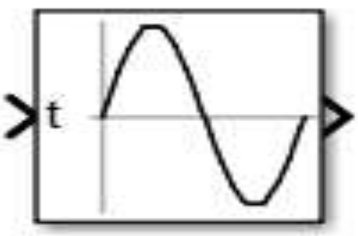

Figure 1 – A sine wave

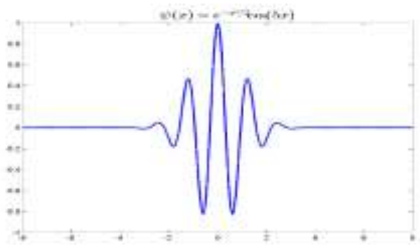

Figure 2 – A wavelet

deficiency by mapping a signal into a two-dimensional function of time and frequency and it analyzes a small section of the signal at a time (called "windowing the signal"). However, the precision of the information obtained is limited by the size of the window. The drawback is that once the size of the time window has been chosen, that window is the same for all frequencies. In order to determine time or frequency more accurately, the researcher would require flexibility in varying the window size (Misiti et al., 1996).

3.2.Fourier analysis v Wavelet analysis

While Fourier analysis involves the decomposition of a signal into sine waves of various frequencies, wavelet analysis is the decomposition of a signal into shifted and scaled versions of the original (mother) wavelet, ψ.[3] A wavelet is a small, irregular and asymmetric wave with finite duration and an average value of zero. On the other hand, sinusoids are smooth, predictable and not limited in duration.[4] Fourier analysis assumes that time series are homogenous in their characteristics, so that periodicity is regular and no exogenous events exist. Any shifts in periodicities would appear as peaks in the spectrum at two different

[3] A scale refers to the width of the wavelet or the distance between oscillations in the wavelet. Scaling refers to stretching or compressing the wavelet. Shifting a wavelet refers to delaying or hastening its onset. Mathematically, delaying a function *f(t)*, that is, a signal, a series, etc., by *k* is represented by *f(t-k)*. (Misiti et al., 1996).

[4] Figure 1 and figure 2 are sourced from www.mathworks.com

frequencies, when only a single process had in fact taken place (Crowley & Lee, 2005). Compared to the smooth sinusoids, these characteristics of wavelets enable the analysis of local features and sharp changes in a signal (Misiti et al, 1996).

The ability to analyse a local area of a larger signal is a major advantage of wavelet over Fourier analysis and its variants. It is able to analyze a local area as the length of the wavelets varies endogenously, stretching into a long wavelet function when measuring low frequency movements and compressing into a short wavelet function when measuring the high frequency movements. When capturing abrupt changes, short functions are required (narrow windows) and when capturing slow and persistent movements, very long functions are required (wide windows) (Aguiar-Conraria et al., 2008). Moreover, it can reveal data characteristics that other signal processing tools would miss such as discontinuities in higher derivatives, breakdown points and trends. It can be applied to higher dimensional data, and compress or denoise a signal without significant degradation (Misiti et al., 1996). Finally, unlike the Fourier method which performs a global analysis, a wavelet analysis does not require any stationarity assumption in order to decompose the time series as it acts locally in time and hence, does not require stationary cyclical components (Gallegati M. , 2008).

3.3.The wavelet transforms

There are two classes of wavelet transforms: the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT) (Grinsted et al., 2004). According to Grinsted et al. (2004) the orthogonal DWT is a concise representation of the data and is useful for noise reduction and data compression whereas the non-orthogonal CWT is better for feature extraction purposes, as the researchers were interested in extracting low signal-to-noise ratio in the time series. Compared to the CWT, the DWT suffers from several drawbacks: the dyadic length restriction for the series to be transformed and that it is non-shift invariant. The maximal overlap DWT (MODWT[5]) was introduced to adress the shortcomings of DWT by giving up its orthogonality and gaining the ability to handle any sample size regardless of whether the series is dyadic or not, increased resolution at coarser scales as it oversamples the data, translation-invariance, that is, the MODWT crystal coefficients do not change if the time series is shifted in a "circular" fashion, and a more asymptotically efficient wavelet variance estimator as compared to the DWT (Crowley & Lee, 2005).

[5] MODWT is also commonly referred to as non-decimated DWT, time-invariant DWT, undecimated DWT, translation-invariant DWT and stationary DWT (Crowley & Lee, 2005).

On the choice between the MODWT and the CWT, an advantage of the MODWT is that it is capable of handling a multivariate analysis. Fernandez-Macho (2012) proposed the wavelet multiple cross-correlations in a single set of multiscale correlations for a multivariate analysis of eleven Eurozone stock market returns. However, Aguiar-Conraria et al. (2008) had argued that the tools provided by DWT and its variants in economic analyses are redundant in some cases. They cited the study by Gallegati and Gallegati on the industrial production of the G-7 countries since 1961 and the use of the MODWT to decompose the industrial production on several scales. In that study, the authors had analyzed the evolution of the volatility of the real economic activity by estimating the wavelet variance at each scale, for each decade separately, instead of using CWT from which the evolution of the variance of the industrial production index at various timescales along the decades could have been immediately inferred and the conclusions extracted within one picture (Aguiar-Conraria et al., 2008). As we would like to map out and examine whether regions in the time-frequency space with high common power have a consistent phase relationship, suggesting causality between the time series, we apply the CWT method to our time series.

3.4. The continuous wavelet transform

A wavelet is a function with zero mean and it is characterized by how localized it is in both frequency and time. The continuous wavelet transform method applies a consecutive series of band-pass filters (wavelets) to the time series (Grinsted et al., 2004). It is defined as the sum over all time of the signal multiplied by scaled (s) and shifted (u) versions of the mother wavelet function ψ (Misiti et al., 1996). The scaling factor controls the length of the wavelet and scaling refers to compression (*If* $|s|<1$) and stretching (*If* $|s|>1$). u refers to location parameter (Tiwari et al., 2015). The CWT results in wavelet coefficients, $W_x(u,s)$, which are a function of scale and location. A time series can be represented as a continuous wavelet transform (CWT) $W_x(u,s)$:

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)dt$$

3.5. Wavelet methods

3.5.1. The wavelet power spectrum

The wavelet power spectrum which gives the measure of local variance is defined as $|W_x(u,s)|^2$. Its statistical significance can be assessed relative to the null hypotheses that the signal is generated by a stationary process with a given background power spectrum (P_k). P_k, where k is the Fourier frequency index, refers to the Fourier power spectrum of a first order autoregressive (AR1) process with lag-1 autocorrelation α (estimated from the time series) and is given by

$$P_k = \frac{1 - \alpha^2}{|1 - \alpha e^{-2i\pi k}|^2}$$

The probability that the wavelet power, of a process with a given power spectrum (P_k), being greater than p is

$$D\left(\frac{|W_n^X(s)|^2}{\sigma_X^2} < p\right) = \frac{1}{2} P_k X_v^2(p)$$

where $_v$ is equal to 1 for real and 2 for complex wavelets (Grinsted et al., 2004). Statistically significant areas at the 5% significance level are bordered by a black bold line.

3.5.2. The cross wavelet transform

The cross wavelet transform (XWT) exposes regions with high common power and reveals information about the phase relationship. The XWT of two time series *x*(t) and *y*(t) is defined as

$$W_{xy}(u,s) = W_X(u,s)W^*(u,s)$$

where * denotes the complex conjugate, and $W_X(u,s)$ and $W_Y(u,s)$ are CWT of x(t) and y(t) (Vacha & Barunik, 2012).

3.5.3. The cross wavelet power spectrum

The cross wavelet power spectrum, defined as $|W_{xy}(u,s)|$ gives the local relative phase between the time series over time and across frequencies (Grinsted et al., 2004). Torrence and Compo (1998) showed that the cross wavelet power distribution between two time series with Fourier spectra P_k^X and P_k^Y is given by

$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X \sigma_Y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y}$$

Where $Z_v(p)$ is the confidence level associated with the probability p for a pdf defined by the square root of the product of two χ^2 distributions.

It should be noted here that the cross-wavelet power spectrum describes the common power without normalization to the single wavelet power spectrum and hence, it is a crude measure of the association between two time series (Tiwari et al., 2015). Further, with the wavelet cross spectrum there is the the possibility of spurious significance tests as it can show strong peaks even for the realization of independent time series (Douglas & J, 2004) . For these reasons, we focus more on wavelet coherence rather than the cross wavelet transform.

3.5.4. Wavelet coherence

Wavelet coherence (WTC) is a measure of the cross-correlation between two time series as a function of frequency and is analogous to the squared correlation coefficient. It can detect regions in the time-frequency space where the time-series co-move but do not necessarily have a high common power. The squared wavelet coherence coefficient is defined as

$$R_{\boldsymbol{n}}^{\boldsymbol{2}}(s) = \frac{\left|S\left(s^{-1}W_n^{xy}(s)\right)\right|^2}{S(s^{-1}|W_n^x(s)|^2)\, S(s^{-1})\left|W_n^y(s)\right|^2}$$

It is the square of the cross-spectrum normalized by the individual power spectra, which gives a quantity between 0 and 1 (Torrence & Compo, 1998). This paper will focus on the wavelet coherency instead of the cross wavelet spectrum as the wavelet coherency is normalized by the power spectrum of two time series.

3.5.5. The wavelet phase

The phase difference (phase lead of x over y) is the angle $\phi_{xy}(u,s)$ of the complex coherency (Aguiar & Soares, 2010). It describes the difference (angle measured in degrees) between two wave forms of the same frequency with respect to time. The wavelet coherence phase difference is given as

$$\phi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}\right)$$

The relative phase relationship is shown by arrows on the WTC plots. The time series are in-phase (out of phase) or positively (negatively) correlated if the arrows are pointing right (left) (Vacha & Barunik, 2012). An arrow pointing vertically upward indicates the second series lags the first by 90 degrees (i.e. the phase angle is 270 degrees). A zero phase difference means that the time series move together at a particular scale (Carey, et al., 2013).

3.5.6. The Cone of Influence

The CWT has edge artifacts because when dealing with finite-length time series, errors occur at the beginning and end of the wavelet power spectrum and padding the end of the time series with zeroes to limit the edge effects introduces discontinuities at the endpoints and decreases the amplitude near the edges as more zeroes enter the analysis. A Cone of Influence (COI) is the region of the wavelet spectrum in which edge effects become important. It is defined as the e-folding time for the autocorrelation of wavelet power at each scale. This e-folding time is chosen so that the wavelet power caused by a discontinuity at the edge drops by a factor e^{-2} of the value at the edge. This ensures that the edge effects are negligible beyond this point. (Torrence & Compo, 1998). The COI is indicated by thin solid lines outside of which paler colors indicate the influence of edge effects and must be viewed with caution (Carey, et al., 2013).

4. Results and discussion

The following discussion refers to WTC figures with quarterly time-scales (32-quarter cycles) represented on the x-axis and the sample period from mid-2007 to early 2015 represented on the y-axis. As mentioned before, arrows indicate the phase difference between the time series – right arrows indicate the series are in phase, left arrows indicate the series are out of phase (180 degrees), and an arrow pointing vertically upward indicates the second series lags the first by 90 degrees (i.e. the phase angle is 270 degrees). Thin solid lines indicate the cone of influence outside of which paler colors indicate the influence of edge effects and must be viewed with caution. Thicker lines bounding areas of red indicate significant coherence at the 95 degree level against red noise (Carey, et al., 2013). The area of time-frequency plot above the 5% significance level is not a reliable indication of causality (Grinsted et al., 2004).

4.1. Real stock returns and inflation

To examine the implication of Fisher hypothesis - that ex post real return on the asset is uncorrelated with the ex post inflation rate – we apply wavelet coherence and analyse the phase difference.

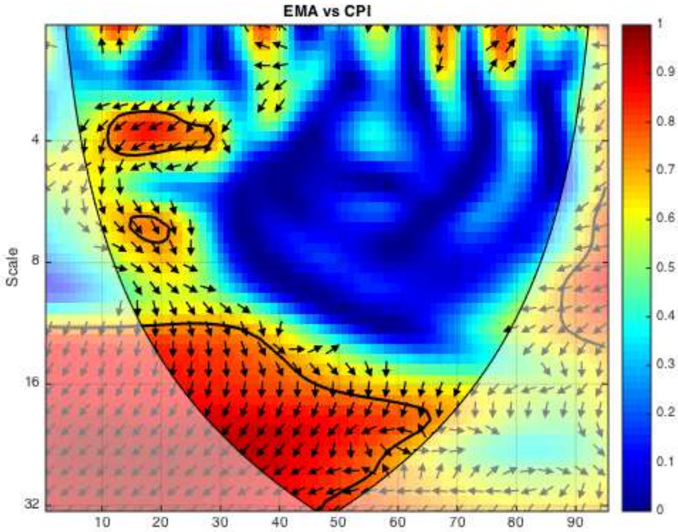

Figure 3 - WTC: Real stock returns and inflation

The WTC of inflation and real stock returns can be seen in Figure 3. It shows large areas of deep shades of blue between 2009 and 2014 corresponding with cycles between 2nd to 12th quarters (6 to 36 month periods) which indicate that inflation and real stock returns are largely uncorrelated in that time-frequency space. However, the high coherency areas between 2009 and mid-2012 beyond the 12th-quarter cycle show significant negative correlation between real returns and inflation, with inflation largely leading real returns. Another area of significant coherence is around the 4th quarter cycle corresponding to mid-2008 and mid-2009 (following the global financial crisis) indicating negative correlation between the series with inflation leading real returns and then a reversal of the lead-lag relationship and the correlation coefficient sign around the 7th quarter cycle with real returns leading inflation.

This figure shows that real returns and inflation are largely uncorrelated below the 3-year horizon but not always independent; and when they are correlated, the dependency is usually negative. However, we are looking at the very long time horizon, meaning that this relationship is not relevant to traders and short term investors, but those who invest beyond 6-month horizons may wish to take note that this relationship is statistically significant in the longer term. These results are not in line with findings by Tiwari et al (2015), Kim and In (2005), who had employed wavelet analysis for Pakistan and the US markets respectively, nor do they confirm the findings of Ibrahim (2011) or Gan (1991) who had employed econometrics methods for the Malaysia case.

4.2.Real stock returns, inflation and economic activity

To examine whether the proxy hypothesis can explain the negative relationship we found in Section 4.1, we apply the same analysis on (i) real stock returns and future economic activity (ii) inflation and real economic activity to see if (i) is positive and (ii) is negative.

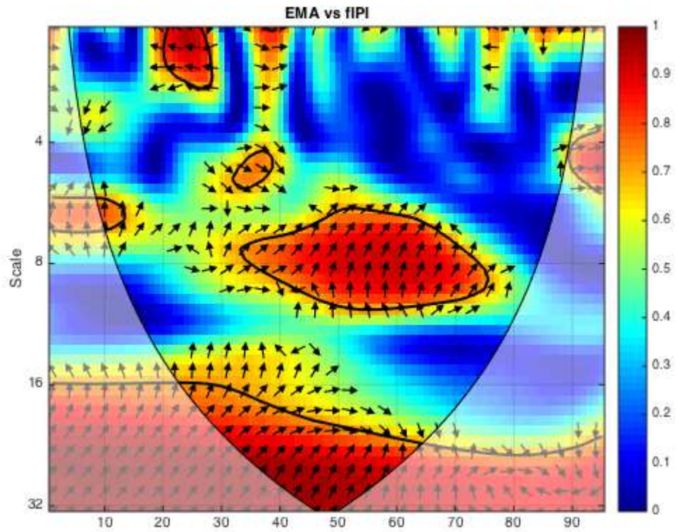

Figure 4 – WTC: Real stock returns and future economic activity

4.2.1. Real returns and future economic activity

Figure 4 depicts scattered areas of significance and all these areas show an in-phase relationship between real stock returns and future economic activity between the first quarter of 2010 and mid-2013 corresponding to cycles of 5^{th} - to 9^{th} -quarters; between 2010 and mid-2012 corresponding to cycles of 24^{th} to 32^{nd} quarters; and between mid-2009 and mid-2011 corresponding to cycles of 16^{th} to 24^{th} quarters. In the first period, real stock returns are leading future economic activity, whereas in the latter periods, future economic activity leads real stock returns.

The time-scales corresponding to these areas are beyond the 1.5-year horizon. It can be seen that below the 6-month horizon real returns are negatively correlated with the future economic activity for a part of 2009 but for the rest of the period in the sample and for the same horizon, they are either uncorrelated or the relationship could be positive but is not significant. The proxy hypothesis relies on the premise that stock returns-real activity relationships are found and that they are positive. However, these

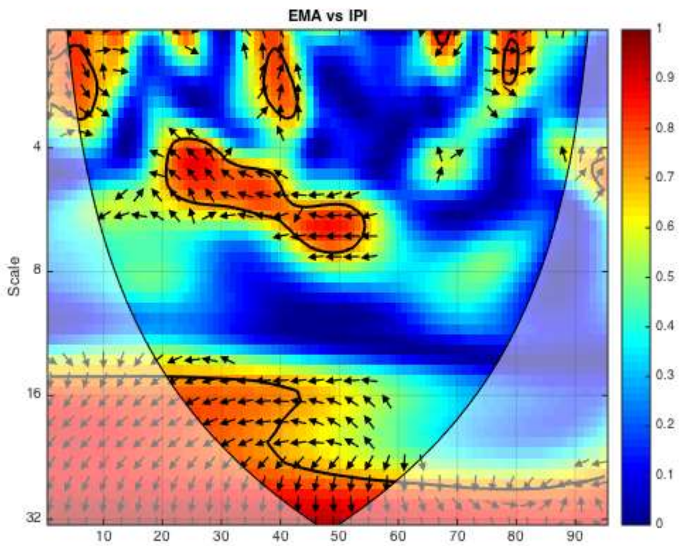

Figure 5 – WTC: Real stock returns and real economic activity

relationships based on a time-frequency analysis, where they are positive, do not correspond to the significantly negative relations in the same time-frequency space between real returns and inflation, except at the higher scales i.e. beyond the 16th-quarter (4-year) cycle. This would mean that the first part of the proxy hypothesis does not appear to be valid based on these data, except beyond the 4-year horizon, although it is prudent to mention at this juncture that a shortcoming of any of these analyses which involves future economic activity is that the actual growth rates of Industrial Production Index are used, as mentioned earlier in Section 3.1.

4.2.2. Real returns and real economic activity

Figure 5 depicts less areas of coherence compared to Figure 4 and the areas between the 16th to30th-quarter cycles between 2009 and 2011 show negative relationship between real stock returns and real economic activity, which is a reversal of the relationship in Figure 4. In the 4th to 5th -quarter cycles corresponding to most of 2009, the arrows indicate that real returns are leading real activity whereas in the between the 16th to the 24th -quarter cycles corresponding to between 2009 and 2011, they indicate that real activity is leading stock returns. Most of the other areas show no correlation between the two series except pockets of areas of significance in the lower scales below the 3rd quarter cycles where the relationship is either positive, and real returns are leading economic activity or the reverse. It seems that the negative relations between stock returns and inflation accompany the negative relations between stock returns and economic activity instead of accompanying stock returns and future economic activity.

4.2.3. Inflation and economic activity.

Figure 6 depicts the WTC between inflation and real economic activity. Most of the area show little to no correlation between the CWTs except around the time-scale from 7th to 9th quarters corresponding to the second quarter of 2008 to the third quarter of 2009 where the area shows significant coherence and inflation leads real activity. Around the 7th quarter, the series appear to be out of phase, indicated by the arrows just outside the significance area. Around the 9th quarter, the arrows shift to indicate the series are in phase.

Figure 7 depicts the WTC between inflation and future real economic activity. This relationship is likewise mostly uncorrelated except between mid-2009 and mid-2010 and from mid-2010 to

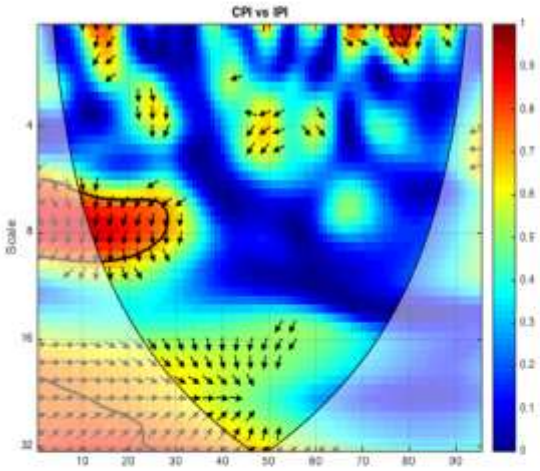

Figure 6 – WTC: Inflation and real economic activity

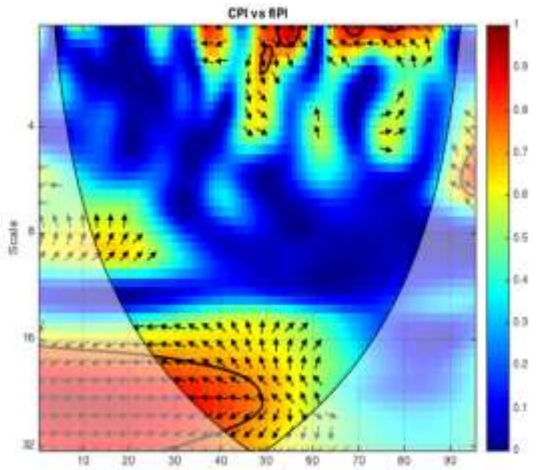

Figure 7 – WTC: Inflation and future real economic activity

mid-2011 corresponding to around the periods 18th to 24th quarters and 24th to 28th quarters respectively when the two CWTs are negatively correlated.

It would appear that the results are consistent with the finding by Gan (1991) and do not lend support to the proxy hypothesis as it does not explain the negative relationship between real stock returns and inflation except for a very limited period beyond the 4th-year cycle and between mid-2009 and mid-2011.

5. Conclusion

It is of concern to investors whether their stock returns can serve as an effective hedge against inflation. A decades-old hypothesis which indirectly posits that stock returns are an effective hedge against inflation has long been studied across many countries but little empirical support has been found for the equation. According to Fisher hypothesis (Fisher, 1930), the nominal return on an asset is the sum of the constant real rate or return on that asset and the expected inflation rate. As nominal returns vary point to point with expected inflation, assuming that the expected real returns are constant, the equation also implies that ex post real return on the asset is uncorrelated with the ex post inflation rate.

This paper investigated the relationship between stock returns and inflation using the FTSE Bursa Malaysia Emas Shariah index and the consumer price index to compute returns and inflation rates respectively, and employs the wavelet analysis, specifically wavelet coherence (WTC) and wavelet phase differences to gain an insight into the relationship between inflation and stock returns on a scale-by-scale (or multi-horizon) basis. They are signal processing tools which can identify local correlation, the relative values of the coherency and local causal relationship between time series in the time domain at different frequencies without having to rely on traditional econometrics methods. This paper appears to be the first in the Malaysian context to employ these techniques on the study of Fisher hypothesis.

The results show that (i) inflation and real returns are largely uncorrelated, even up to the 3-year (12^{th} –quarter) horizon, except for the 2 years post financial crisis (ii) beyond the 3-year horizon WTC shows significant correlation between the series, an area that is not relevant to many investors and relevant only to very long-term investors (iii) where inflation and real returns are found to be negatively correlated, Fama's proxy hypothesis is not supported by the WTC between stock returns and future economic activity (iv) the negative relations between stock returns and inflation accompany the negative relations between stock returns and economic activity instead of accompanying stock returns and future economic activity (v) inflation and future economic activity as well as inflation and economic activity are mostly uncorrelated, negating the possibility of explaining the negative relations between inflation and stock returns over very long horizon. These results indicate that investors in the Malaysian Shariah index can expect some hedging effects of their stocks against inflation at any investment horizon up to 3 years. Beyond that, investors must be cautious as stock returns may not provide any hedging ability. These results are not in line with the findings by Gan (1991) and Ibrahim (1991) who had employed econometrics methods in their study of Fisher hypothesis.

As mentioned, a shortcoming of the analyses involving future economic ability is in the use of actual growth rates of economic activity, as it is beyond the scope of this paper to construct a macro model to determine anticipated real activity. Future research could involve constructing such a model, include an analysis between nominal returns and inflation, as well as decomposing inflation into expected and unexpected components using volatility measures to analyse hedging effectiveness.

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