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The beta heuristic from a time/frequency perspective: A wavelet analysis of the market risk of sectors[☆]

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ABSTRACT

Wavelet methodology is used to estimate scale betas for eleven industry/sectors for the period 1986-2016. A comparison of scale betas with standard regression estimates of betas finds no significant differences for any of the sectors at high frequency/low scales. However, for most of the sectors there are significant differences at medium and high scales. A rolling 60 month window shows that scale betas may differ from standard betas substantially for several years. Implications for portfolio managers, especially those employing beta rotation strategies, are provided.

1. Introduction

The market exposure of an investment is a well-recognized source of risk that portfolio managers must take into account. The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Linter (1965), and Mossin (1966) continued the path breaking research of Markowitz (1952) on the risk reducing effects of portfolio diversification by introducing beta, a measure of systematic risk that captures the non-diversifiable risk of an investment. The degree that market exposure captured by beta does the job of assessing risk well has been subject to a great deal of research. Whether or not a consensus regarding the best approach to defining and estimating market risk is reached, for portfolio managers beta is a fact of life. For this reason, we view the widespread use of beta as a measure of an investment's systematic or non-diversifiable risk by investment managers similar to that of a decision-making heuristic.[1] In this case, a short-cut method for understanding and comparing market risk across investments. As Bollerslev et al. (2016) comments, “Even though numerous studies over the past half-century have called into question the ability of the capital asset pricing model(CAPM) to fully explain the cross-section of expected stock returns, the beta of an asset arguably remains the most commonly used systematic risk measure in financial practice.”[2] Another fact of life for portfolio managers is the existence of investments in sectors done relatively cheaply through ETFs or mutual funds.[3,4] Khorana and Nelling (1997) find that the most important factor explaining variation in sector-fund returns is the return on the market index.

The presence of both short and long-term market participants is another fact of life for the investing world. Reconciling this fact with estimates of beta is not something that at least on the intuitive level one would think that standard CAPM regression-based estimates of beta does well. This is because the standard market beta is based on

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[1] There is a large literature on heuristics in decision making. An excellent overview is found in Kahneman (2011).

[2] p. 464

[3] Based on data from the Investment Company Institute (May 2016) 334,965 million is invested in U.S. sector/industry ETFs. A recent IMF report on the Asset Management Industry (2015) provides evidence of the growth of focused investments.

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assumptions that place restrictions on time horizons and frequency changes.[5]

Wavelet methods have gained widespread acceptance as an efficient means of investigating multi-horizon properties of time series. Wavelets provide a unified framework for investigating the relationship among variables across frequencies and over time.[6] Recent research that offers empirical support for time-scale differences among investors in equity and commodity markets is found in Vacha and Barunik (2012), Aloni et al.(2013), Bekiros and Marcillino (2013), Graham et al. (2013), and Bekiros et al. (2016). Rua and Nunes (2012) use wavelet methodology and provide evidence that market risk varies across time and over frequencies.[7] Huang and Hueng(2008) estimate a time-varying beta model applied to the ten S & P 500 sectors, but do not consider time-varying behavior at different frequencies.[8] Our paper differs from previous research in that we investigate the market risk of sectors through the use of a well-accepted methodology for dealing with time-scale differences.

In this paper, we estimate betas for eleven market sectors using wavelet analysis and compare wavelet betas with standard regression-based betas. One result is that for all eleven sectors, low scale betas (2-4 months) are not significantly different from standard betas. However, when it comes to medium and high scale betas (we use six scales that range from 2-128 months, where the highest frequency or lowest scale is 2-4 months) we find a different story in that all but one of the sectors has at least one scale beta significantly different from the standard. As our analysis illustrates the differences that are found to be significant at medium and high scales vary depending on the sector and scale. The one sector without any significant differences between scale and standard beta is a high beta sector, Business Equipment. In our analysis whether or not there are significant differences between standard regression estimates of beta and scale betas appears consistent with the story told by the wavelet coherence plot (wavelet coherence is a measure like correlation, but localized in time-scale space and not limited to linear dependencies). In the case of Business Equipment, as our coherence plot illustrates there are no breaks in coherence even over medium and high scales.

Although there are a number of reasons to estimate beta coefficients for sectors with a methodology that captures multi-period investment horizons, we find that at low scales it does not matter, while for most sectors at medium and high scales it does. For portfolio managers our results can be used to turn the beta dial in a direction that helps improve its use. For example, portfolio managers who use beta rotation strategies that rely on low beta sectors as protection against market downturns should use scale betas that reflect horizon effects. As our rolling window estimates of scale betas at medium scales illustrate for widely recognized low beta sectors such as utilities and health, time-scale considerations have significant effects on beta estimates.[9] We also find sectors such as Telecom that switch from a low beta category using the standard beta estimate to a high beta category based on scale betas estimated at higher scales, and a sector, Manuf, that switches from a high to low beta category.

While it is not controversial to assert that supply and demand shocks impact sectors at different times or horizons, this fact is not sufficient for generating low scale betas that are significantly different from standard estimates. We are applying wavelet methodology, a methodology that captures horizon effects applied to a context where there exist factors driving sector returns that work over multiple horizons, but do not find significant differences between scale and wavelet betas at low scales. Wavelet methodology captures unique information at each horizon, and we surmise that high frequency changes are not contributing to market risk at the sector level perhaps because high frequency changes represent short-lived shocks that are more likely to reflect diversifiable risk that is not captured in estimates of beta coefficients. This is not the case at high and medium scales. The medium and high scale dynamics play out differently in that for ten of the eleven sectors there is at least one and as many as four scale dependent betas that are significantly different from the standard estimates. We argue that there are changes in the market environment occurring at medium and high scales that differ in important ways from changes at low scales. However, the time and frequency changes occurring at medium and low scales are not all created equal. Some changes do lead to scale dependent betas that are significantly different from standard estimates, but not every scale beta at medium or high scales is significantly different. We relate this to whether there are coherence differences across medium and high frequencies.

Differences in estimates of scale betas and standard betas across sectors are also compatible with Siegel (2005) where he argues that the diffusion of market moving information within sectors and across sectors is uneven. His explanation is compatible with our results since such unevenness may be captured by changes in coherence across frequency that wavelet analysis uncovers. Put differently, since wavelet analysis captures changes in the frequency domain over time we are able to identify periods or scales when estimates of the systematic risk of sectors are significantly changed relative to standard estimates of beta. Wavelet measures of market betas for the sectors provide significantly different measures of market betas estimated from the standard one-factor market model when the frequency resolution of low frequencies and the time resolution of high frequencies are important features of the underlying risk dynamics. We find this occurs when there are large differences in coherence across frequencies. Our finding that the standard market beta of the business equipment sector for the period examined (1986-2016) is not significantly different from scale betas even at medium and high scales is explained by its high, but stable coherence over the period examined.

This paper employs a data set that includes the following periods of high market volatility: 1) Asian Crisis of 97-98, 2) tech bubble burst of 2000, 3) financial crisis of 2008-2009, and 4) the European debt crisis (2010-2011).[10] Our analysis of the data also highlights through results from a Multiresolution Analysis that periods of market turmoil are associated with high market volatility at low scales, but only the financial crisis of 2008-2009, followed by the European Debt Crisis is associated with periods of high market volatility at high scales. The presence of high market volatity at high scales we refer to as a ”market turn,” while a ”market shrug” refers to high market volatility at low scales. An examination of the wavelet power spectrum for the market and each sector illustrates that the pattern of variation among sector returns even during periods of market turmoil, appears differently at different time horizons and frequency intervals. Some of these periods are market shrugs affecting few sectors, while market turns are felt across many sectors over many different scales.

The remainder of the paper is organized as follows: Section 2 highlights research based on wavelet analysis in applied financial economics of particular relevance for our analysis. The important concepts used in wavelet analysis that are applied in our analysis are

[5] A voluminous literature devoted to empirical tests of the CAPM evolved. Much of the empirical work on the CAPM employs a beta that remains constant over time or over the estimation period. One fix for this is found in time-series variation in the conditional betas of equity portfolios as shown in research by Bollerslev et al. (1988). Recent research by Bali (2008) have expanded the seminal inter-temporal capital asset pricing model (ICAPM) found in Merton (1973) using novel econometric techniques.

[6] Wavelet methodology has been employed across research fields, with growing applications in economics and finance, see Conlon and Cotter (2011). Research on wavelet methodology of particular relevance for our paper is discussed in the next section.

[7] Their application is to Emerging Markets.

[8] Their focus is on the asymmetric risk-return relationship and they do not employ wavelet analysis.

[9] See ?Business Cycle Approach to Equity Investing? by Fidelity Investments(2014).

[10] These periods of high volatility have been identified as periods of crisis in such research as Bekiros et al. (2016).