DOES THE RISK MATCH THE RETURNS: AN EXAMINATION OF US COMMERCIAL PROPERTY MARKET DATA

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ABSTRACT

Evidence from the US Commercial property market suggests periods of extended stable performance are generally followed by large concentrated price fluctuations. This extreme volatility may not be fully reflected in traditional risk (standard deviation) calculations. This research studies 38 years of NCREIF commercial property market performance data for normal distribution features and signs of extreme downside risk. Methodology covers the recognised Z Test and the fractal geometry, Cubic Power Law instrument. For the reporting of annual returns on quarterly figures, the industry preferred investment performance measure, the results showed the data to be both asymmetric, and being taller and narrower than a normal bell curve distribution with fat dumb bell downside tails at the perimeter. In highlighting the challenges to measuring commercial property market performance, the research revealed a better analysis of extreme downside risk is by a Cubic Power Law distribution model, being a robust method to identify the performance of an investment to the vulnerabilities of serve risk. Modelling techniques for estimating measures of tail risk provide challenges and have shown to be beyond current risk management practices, being too narrow and constraining approach.

Keywords: Extreme risk, Standard deviation, Commercial property market performance, Power Law distribution

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1. INTRODUCTION

The investment industry principally measure the performance of commercial property alongside competing asset classes by recognised mathematical models of annual return (mean) and risk (standard deviation). These statistical approaches provide the backbone for the banking and finance community to compare the performance across asset classes, and importantly the foundation for leading investment strategies: risk adjusted returns, sharpe ratio, capital asset pricing model and modern portfolio theory. There is increasing evidence that while these models work well under stable conditions, they can fail when stable assumptions cease to hold and extreme volatility occurs.

Knowledge in this area is really important for property professionals as it impacts on asset allocation strategies and portfolio management. Inaddition, commercial property low liquidly and high value thresholds requiring debt funding can dramatically increase the likelihood of financial ruin if measurements of extreme market risks are overlooked.

The stable environment for modern financial theory to successfully operate is far from actual market conditions. Historical evidence shows extended stable periods and then extreme volatility from major unpredictable events, creating large concentrated negative price fluctuations. These major downside risk events are inherent to many markets, including commercial property, and are often outside the realm of regular expectations. Commonly referred to in literature as statistical outliers (outside ± 2 standard deviations), these downside risk events frequently have a combination of low predictability and large impact resulting in significant financial loss.

Increasingly, leading theorists and practitioners have recognised that the frequency and magnitude of these extreme events should be a key financial market consideration. Whilst these occasional and unpredictable large deviations are rare, they should not be dismissed as “outliers” because, individually and cumulatively, their impact is so dramatic that they can spell disaster to an individual, organisation or a nation well beyond their ability to recover from in the short term (Buchanan 2013).

In detailing the behaviour and new approaches to the financial market, the commercial property market is still to be examined as to the analysis of past extreme negative price movements and the implications for financial ruin. This research studies 38 years of quarterly US commercial property market performance data for signs of extreme risk. As a valuation based index, it is recognised that the data is smoothed, however to follow industry commentary and analysis the research examined the annual returns on a quarterly basis. This is a similar measure to the transaction based indices of competing asset classes.

Following this introduction, Section Two provides a literature review covering the quantitative measures of risk, issues with extreme values and Power Law. Section Three details the selected commercial property data and associated methodology. Section Four provides the empirical findings and the implications for property fund managers and the investment community. The last section provides the concluding comments.

2. LITERATURE REVIEW

Louis Bachelier, a 19th Century French physicist, is regarded by many as having developed the mathematics of the modern financial markets. He discovered that market prices move randomly and that a likely future value can be calculated from a normal distribution (bell curve). He suggested that most future values will be somewhere near the centre (tallest part of the curve), and further out from the center peak the curve drops off quickly, indicating that large changes in price are less likely (Weatherall 2013).

The distribution around the tallest part of the curve represents a measure of volatility and is the yardstick to measure financial risk. As Wheelan (2013) explained, the standard deviation statistic is represented by the Greek letter sigma, "σ" and shows the variation of dispersion from the mean. Plotted on the conventional bell curve, the standard deviation distribution is shown in Figure 1.

Figure 1 **Normal Distribution**

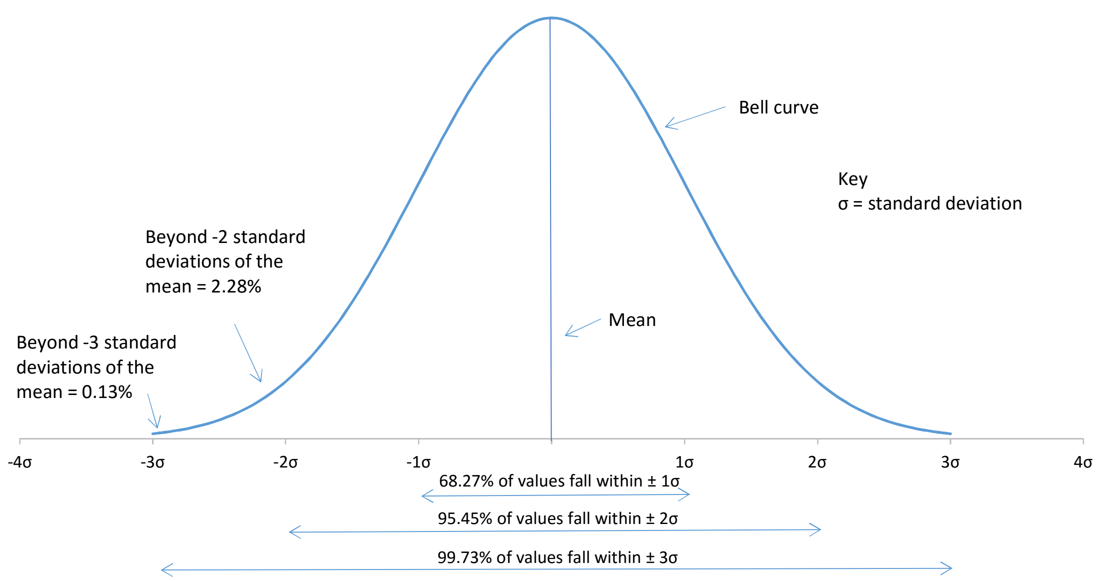

Figure 1 illustrates the bell curved shape of a normal distribution. The standard deviation "σ" marks the location of the values, with 68.27% of the values within one standard deviation of the mean, similarly 95.45% of the values are within two standard deviation of the mean and nearly all (99.73%) of the values are within three standard deviation of the mean. As the sigma "σ" grows, the odds of being inside the bell curve rapidly approaches 100%, while the odds of being outside, an "outlier" (beyond ± 2 standard deviations), should be an extremely rare event (Wheelan 2013).

In defining the normal distribution on a bell curve, the possibilities of unpredictable large deviations (outliers) are simply marginalised, because the data over-sampled the good times and under-sample the bad ones. This situation can occur in the finance market with long stable periods providing extensive data close to the mean and then, although rare, severe instability with huge fluctuations creating booms and crashes. These extreme events far from the centre of the distribution are more regular than a normal distribution would predict and create, so called, "fat tailed" distributions (Mandelbrot and Hudson 2008).

These extreme events now form an important new area of research and are predominately caused as a consequence of large unexpected shocks. These shocks include natural catastrophes (superstorms, pandemics (SARS) and tsunamis etc) and man-made disasters (investment strategies (GFC), technological (Chernobyl) and acts of terrorism etc) have been labeled as Black Swan Events. Major Black Swan Events can severely challenge economic activity, social cohesion and political stability and cascade across global systems, irrespective as to whether or not they arise within health, climate, social or financial systems (Higgins 2013, Silver 2012, Taleb 2009).

Measures of extreme risk provide skewed distribution, as evident in the financial markets which rarely follow a normal bell shaped distribution. The higher frequency of extreme outcomes in the tails of the distribution may lead to an underestimation of risk. In such cases, Power Law (also known as the Pareto Distribution) may be a more appropriate model to measure fat-tailed distributions. This technique is often used in applications of extreme value theory as it overcomes many of the shortcomings of traditional financial stress testing (value at risk) models (Mandelbrot and Hudson 2008, Powell 2008).

In practical terms, conventional distribution calculations are best suited for a data series that exhibits mild and well-behaved randomness, as the difference between each point and the mean is squared and so leads to an equitable scattering of points evenly around the mean. Power Law on the otherhand, utilises fractal patterns which can relate intensity to frequency and so is more suited for data series that can exhibit irregular large movements. Such Power Law formulas are commonly used in science, for example: seismologists use mathematical models that show the intensity of earthquakes varying in accordance with Power Law. The well-known Richter scale and the more recent Moment Magnitude Scale are based on Power Law equations (Damodaran 2008, Mandelbrot and Hudson 2008, Wheelan 2013).

For investment strategies, Power Law can define the probability of a rare event as it provides the parameter that determines the shape of the distribution, and therefore the likelihood of given extreme events. The Power Law exponent varies inversely with the fatness of the downside tail distribution, being the fatter the tail, the greater the likelihood of a given extreme loss (Mandelbrot and Taleb 2006, Powell 2009).

3. PROPERTY DATA AND METHODOLOGY

For this study, the National Council of Real Estate Investment Fiduciaries (NCREIF) Property total return Index series provided quarterly (unleveraged) returns on the American commercial property market covering a 38 year period: 1978 to 2015. As this is a valuation based index, there is evidence of reduced volatility when compared to transaction based indices. The smoothing (autocorrelation) primarily occurs with the frequency of the property valuations, with individual property valuations anchored to prior property transaction data in the absence of conclusive current property market evidence of significant change (Marcato and Key 2007).

Whilst there is evidence of autocorrelation (AC(1) 0.78) for the property data series, industry commentary and analysis traditionally measures performance by annual returns (year on year) on a quarterly basis. This is a measure conventionally used across the competing investment class transaction based indices and selected for this property investment industry focused research paper.

As extreme price swings appear to be the norm in current financial markets, Power Law distributions can provide valuable information on equity market outliers. This needs to be examined relative to competing asset class returns, to see if extreme outliers exist and have features which follow the Power Law distribution. This research covers the key US commercial property asset class.

4. RESULTS

The first step is to examine the annual returns on the quarterly commercial property market total return performance data. Descriptive statistics provide a simple summary of the selected data as shown in Table 1.

Table 1 **Descriptive Statistics**

	Commercial Property Market Annual Total Returns December 1978 to December 2015
Mean	9.56%
Standard Deviation	7.77%
Median	10.99%
Skewness	-1.58
Excess Kurtosis	3.41
Mean -1 SD	1.78%
Mean - 2 SD	-5.99%
Mean +1 SD	17.33%
Mean +2 SD	25.10%
Range	44.57%
Maximum	22.47%
Minimum	-22.11%
Count	149

Table 1 highlights the average quarterly total returns of 9.56% and a relatively high standard deviation of 7.77%. This indicates that the data points are spread out over a large range of values as evident by the maximum (22.47%) and minimum (-22.11%) with the furthermost extreme negative data point well outside - 2 standard deviation. Interestingly, this spread is not supported by a high 3.41 excess Kurtosis reading which suggests the data are clustered close to the mean with some values lying at the extremities of the distribution. This gives an impression that the data appear to be taller and narrower than a normal distribution with fatter (heavier) tails.

In addition, as the 10.99% median is above the 9.56% mean, the data appear asymmetric (uneven) with more data points on the right side of the mean. This contrasts to the -1.58 skewness reading which indicates that the tail on the left side is longer than the right side. It is this negative tail on the distribution curve that highlights extreme downside risk values with damaging big swings that can lead to financial ruin.

In detailing the descriptive statistics, a bar chart provides the visual analysis that can better show the distribution of the data, see Figure 2.

Figure 2 **US Commercial Property Market Annual Total Returns: Histogram of Quarterly Data Distribution**

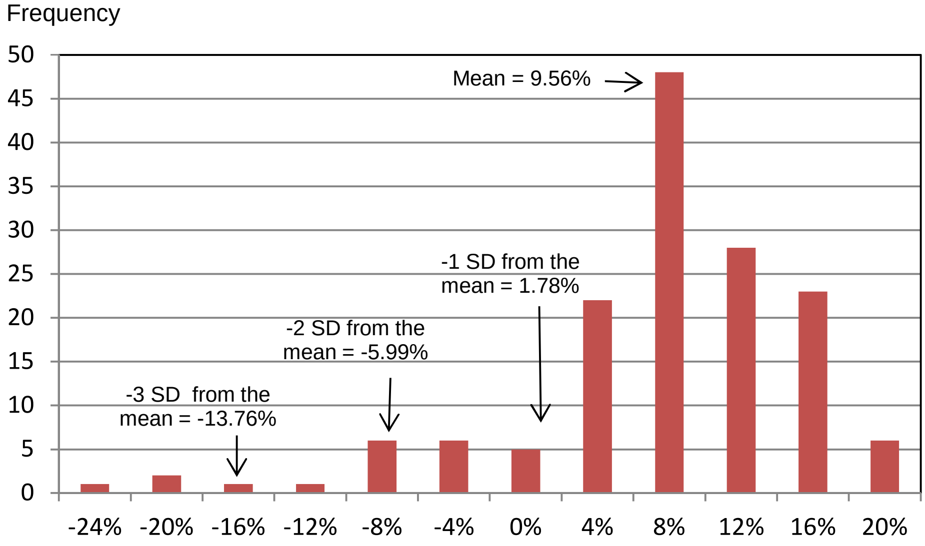

Figure 2 shows a histogram of the data distribution for the asymmetric annual total returns from the quarterly commercial property market performance. Whilst the data are clustered close to the mean with more values on the right side, it is the spread to the extremities which highlight the uneven distribution with several outlier values beyond ± 2 standard deviations (95.45%) from the mean. The number of these extreme values outside - 2 standard deviations gives a dumb bell downside feature (fat tails) to the asymmetric bell curve distribution. This is a common characteristic when examining extreme risk, most importantly on the left side of the distribution covering the dangerous downside values at the end of left curve, which more often highlight events leading to financial ruin.

As the negative distribution is important to examining downside risk, Table 2 compares the actual downside quarterly commercial property total return values to the standard bell curve distribution from the mean for the NCREIF 149 data points.

Table 2 **Downside Risk Comparison: Normal Bell Curve Distribution Values to Actual Commercial Property Total Returns**

	Normal Distribution	Actual Data	Variation
Mean to -1SD	51	40	-11
-1SD to -2SD	21	11	-10
-2SD to -3SD	3	4	1
-3SD >	0	4	4

Table 2 compares the spread of the actual data points to that for a standard bell curve distribution. It is evident that there is a lack of actual data points between -1SD and -2SD data with the excess occurring on the extremities (beyond -2SD). The mean to -1SD variation highlights the skewness of the data when comparing the normal bell curve downside distribution (75 data points) to the actual downside distribution (59 data points). This shows the contrast between stable market conditions and periods of large negative price movements.

The periods of extreme risk can be magnified in the commercial property markets with:

i) Limited exit options. Unlike public equities, commercial property has low liquidity, high transaction costs and no formal market clearing mechanism (Crosby and McAllister 2004).

ii) High value threshold. Commercial property investment requires significant levels of capital investment, which can be achieved by increased equity leading to high specific property risk or more often, debt financing forming a key property investment component. Whilst debt funding can improve property investment returns, it substantially increases the risk (Higgins 2014).

In identifying the actual commercial property data spread, the likelihood of the extreme values occurring on a normal bell curve distribution can be measured by a Z-test. Table 3 shows the probability of the ten outermost values occurring.

Table 3 **Standard Bell Curve Distribution and Event Probability**

	Data	Standard Deviation	Z Score table	Probability 1in	Event Year
1	-22.11%	-4.07	0.00%	43,173	10,793
2	-19.57%	-3.75	0.01%	11,172	2,793
3	-16.86%	-3.40	0.03%	2,948	737
4	-14.68%	-3.12	0.09%	1,100	275
5	-9.60%	-2.46	0.69%	146	37
6	-6.75%	-2.10	1.80%	56	14
7	-6.64%	-2.08	1.86%	54	14
8	-6.46%	-2.06	1.97%	51	13
9	-5.66%	-1.96	2.51%	40	10
10	-5.59%	-1.95	2.57%	39	10

Table 3 points to a disconnect between the standard bell curve distribution and the actual commercial property market total returns. The furthest actual negative value -22.11% represents a -4.07 standard deviation reading, which on the Z test table for a one tailed downside distribution shows a 1 in 43,173 chance of the event occurring, being an unrealistic 1 in 10,793 year event.

Conversely, taking the calculated mean (9.56%) and standard deviation (7.77%) for the 38 years of actual annual returns for quarterly commercial property market total data (149 data points), the Z test for a one tailed downside distribution calculates the furthest negative value at -9.54%. Measured to the mean, this is a 57% difference to the actual worst negative value of -22.11%. The shortfall highlights the limitations of the standard deviation model to be a measure of extreme risk where the data exhibits asymmetric fat tailed distribution features.

The issues associated with measures of extreme volatility using the standard bell curve distribution is extensively documented in the equity market literature: see Mandelbrot and Hudson (2008), Taleb (2009) Weatherall (2013). The recognised approach for stockmarket activity is to follow a Power Law distribution with an exponent of three (3) beyond ± 2 standard deviations. Table 4 shows the consequence of Cubic Power Law application to the ten outermost negative values.

Table 4 **Cubic Power Law Distribution and Event Probability**

	Data	Standard Deviation	Power Cube	Probability 1in	Event Year
1	-22.11%	-4.07	0.27%	372	93
2	-19.57%	-3.75	0.35%	290	73
3	-16.86%	-3.40	0.46%	216	54
4	-14.68%	-3.12	0.60%	167	42
5	-9.60%	-2.46	1.22%	83	21
6	-6.75%	-2.10	1.97%	51	13
7	-6.64%	-2.08	2.01%	50	13
8	-6.46%	-2.06	2.08%	49	12
9	-5.66%	-1.96	2.43%	42	11
10	-5.59%	-1.95	2.46%	41	10

Table 4 illustrates the Cubic Power Law of returns. The probabilities of extreme events occurring, especially the prominent outliers are substantially improved to near realistic levels. Below -3 standard deviation reading to the mean the chances imposed converge to the normal distribution curve. This is evident in the similar readings for data points 6 to 10 in Table 3 and Table 4.

While scalable laws do not yet yield precise results, Cubic Power Law model can be an extremely robust method to identify the performance of an investment to the vulnerability to severe risk, where extreme values are more common than a normal distribution implies. This fundamentally quantifies distributions that have “fat tails”, namely, a higher probability of extreme values that can have a significant impact on long term performance (Mandelbrot and Taleb 2006).

In demonstrating extreme risk, this risk measure should be separated from the traditional standard deviation risk model. Also whilst this research examines commercial property returns, the asset class should not be considered in isolation as alternative investments could exhibit similar features. This is evident by Mandelbrot and Hudson (2008), Silver (2013) and Weatherall (2013) research on the American stockmarket, all showing that a normal bell curve distribution does not effectively account for extreme price movements and that equity markets are wildly random.

In providing a platform for research on commercial property and extreme risk, there are potential areas of further study, namely:

i) Benchmark tracking of the selected property market index is extremely difficult to achieve, and depending of tracking error would require numerous properties and beyond many investor’s capabilities, see Callender et al (2007).

ii) With high value thresholds, commercial property investment generally requires considerable equity and debt funding. Whilst debt funding can improve property investment returns, it increases volatility and hence exposure to the likelihood of extreme risk values, see Higgins (2014).

iii) Illiquidity issues are key characteristics of commercial property and impact on performance. Decisions need to review low reading data points both in isolation and the surrounding returns, which may provide a different performance perspective.

iv) As commercial property return indices operate in a data scarce environment, the extreme risk profile may vary to an asset class (equity market) with high frequency transaction data bases (Bokhari and Geltner 2010).

Modelling techniques for estimating measures of extreme downside risk provide challenges and have shown to be beyond traditional risk management techniques being too narrow and constraining a definition. Analysis of downside risk should form a key part of the property decisions, and mathematical approaches to extreme volatility be included in the property investment manager’s toolkit. Measuring extreme risk is the first step in analysing and dealing with risk in both an asset class and portfolio context.

5. CONCLUSION

Modelling techniques for estimating measures of extreme downside risk provide challenges and have shown to be beyond traditional risk management techniques being too narrow and constraining a definition. Analysis of downside risk should form a key part of the property decisions, and mathematical approaches to extreme volatility be included in the property investment manager’s toolkit. Measuring extreme risk is the first step in analysing and dealing with risk in both an asset class and portfolio context.

This research studies 38 years of US Commercial property market annual total returns on the quarterly performance data for normal distribution features and signs of extreme downside risk. The results show that the data appears to be asymmetric, being taller and narrower than a normal bell curve distribution with fat dumb bell tails at the left perimeter. There is a disconnect between the standard bell curve distribution and the actual commercial property market total returns. This is demonstrated by the furthest actual ungeared negative value -22.11% representing the probabilities of an unrealistic 1 in 10,793 year event occurring. Alternatively, the Cubic Power Law of returns substantially improved the probabilities of extreme events occurring with a realistic 1 in 93 year event.

In context, forward looking property professionals, more than ever, need to understand, measure and manage all aspects of risk - prominent investors expect this. Those that can meet the challenge are more likely to be in a better position to succeed and prosper in an increasingly dynamic global environment where extreme volatility events are the new normal. The first step in the journey is to appreciate and support leading property research in this area.

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