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EDITORS
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AUT Business School
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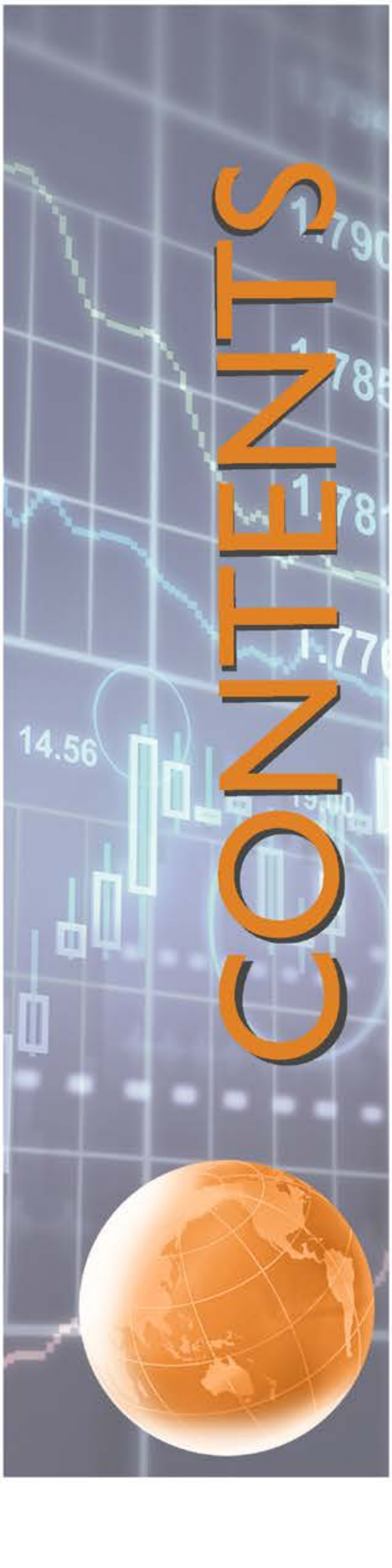

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RETURNS TO LOW RISK INVESTMENT STRATEGY

MAYANK JOSHIPURA[1], SHILPA PESWANI*[2]

1. NMIMS University, Mumbai, India
2. NMIMS University and St. Francis Institute of Management and Research, Mumbai, India

* Corresponding Author: Shilpa Peswani, Assistant Professor and PhD scholar at NMIMS University and Asst. Professor at St. Francis Institute of Management and Research, Mount Poinsur, SVP Road, Borivali (W), Mumbai-400103, Maharashtra, India.
☎ +91 720 874 4515 ✉ shilpaphddata@gmail.com

Abstract: The paper studies the low-risk anomaly in the Indian equity market represented by stocks listed on National Stock Exchange (NSE) for the period January 2001 to June 2016. The study provides evidence that low-risk portfolio returns are robust across various risk measures as well as market cap buckets though the intensity of the returns differs. The returns from low-risk investment are not only economically but also statistically significant. They outperform the high-risk portfolio as well as the benchmark portfolio. They deliver higher returns even after controlling for the well-known size, value and momentum factors. The returns are highest for low-risk large cap stocks portfolio sorted for stock volatility as a risk measure. Most of the low-risk portfolios consist of growth and winner stocks. The study provides a framework for an implementable low risk investing strategy.

Keywords: low risk anomaly, volatility effect, idiosyncratic risk, market efficiency, beta.

1. Introduction

The basic goal of portfolio management is to provide higher returns for a given degree of risk or deliver a certain level of return for lower risk. To meet this goal, academics and portfolio managers have formulated various investment strategies. An investor needs to take high risk to earn higher returns – this conviction has survived from the time finance theory led by CAPM has evolved as a structured body of knowledge. But empirical evidence started mounting challenging positive risk-return relationship within the asset class and it was refereed as low risk anomaly where the low-risk investments delivered high returns. Investments in low volatility stocks have delivered higher risk adjusted and absolute returns over a period of time across global markets than high volatility stocks and value weighted benchmark portfolios. It has attracted enough attention for further investigation and application in portfolio management.

Thus, the objective of this research is to provide answers to the following research questions:

1. Does low-risk anomaly exist in the Indian stock market? Is it significant?

2. Is the strength of the low-risk anomaly sensitive to the choice of risk measure?

3. Is the strength of the low-risk anomaly sensitive to the market cap size buckets?

4. How strong is the low-risk investment alpha after controlling for the value, size and momentum factors?

The study considers three risk measures to construct portfolios – volatility (TVOL), idiosyncratic volatility (IVOL) and CAPM beta (Beta). The standard deviation of returns of a stock measures volatility (total risk). CAPM beta measures systematic risk while idiosyncratic volatility measures firm-level unsystematic risk.

The study establishes the following for the Indian equity market: (a) Returns from low-risk stocks portfolio exceed high-risk stocks portfolio returns as well as equally weighted benchmark market portfolio returns over the full market cycle on risk adjusted basis. These returns are positive, as well as statistically and economically significant. (b) Return to low-risk investment strategy is independent of market cap size and the risk measure used to construct portfolios though the intensity of returns differs. (c) Low volatility investing gives higher returns than low idiosyncratic risk investing or low beta investing. (d) Considering the market cap bucket, a low volatility large cap portfolio delivers highest positive excess return. (e) The low beta small cap portfolio delivers negative excess returns. (f) Low-risk investment gives positive excess returns even after controlling for size, value and momentum factors. (g) The low-risk portfolio mostly consists of growth and winner stocks.

Early evidence of low-risk anomaly was documented back in 1970s. Low-risk anomaly indicates that over a period of time, safer stocks (low risk) deliver higher risk adjusted returns than riskier stocks. A flatter than expected risk-return relationship was documented by Black, Jensen, and Scholes (1972). Haugen and Heins (1975) report early evidence for negative risk return relationship. Later, Fama-French (1992) explained that only beta as a systematic risk measure failed to explain the flat market line. They introduced the size and value factors.

Studies on low-risk anomaly differ on the ground of method of portfolio construction and the choice of risk measure. The three common risk measures found in the literature are volatility, idiosyncratic volatility, and CAPM beta. The two portfolio construction approaches are ranking stocks using a risk measure or constructing a minimum variance portfolio using Markowitz (1952) framework. There are studies that either explain the low-risk anomaly or refute it. The possible explanations for the low-risk anomaly can be categorized into economic and behavioural aspects.

Studies conducted by Haugen & Heins (1975), Blitz and Vliet (2007), Clarke, De Silva and Thorley (2006), Ang, Hodrick, Xing and Zhang (2006, 2009), Baker, Bradley and Wurgler (2011), Soe (2012), Baker and Haugen (2012), Blitz, Pang and Vliet (2013) and Frazzini and Pedersen (2014) found that the historical returns of low-risk securities were higher than high-risk securities.

Refuting the above, the studies conducted by Malkiel and Xu (1997), Malkiel and Xu (2002), Fu (2009), Spiegel and Wang (2005), Martellini (2008) support the view that high-risk stocks give higher average return though it varies over time. Bali and Cakici (2008) attribute inverse relationship between idiosyncratic risk and return to illiquid, small stocks. Bali, et al. (2011) attribute the negative risk-return relationship due to investor's demand for lottery like pay-offs. Scherer (2011) argues that excess returns of a minimum variance portfolio are attributable to size and value factors and volatility effect is merely a proxy for value effect.

Black et al. (1972), Frazzini and Pedersen (2014) and Hong and Sraer (2012) attribute the existence of a flat relationship between risk and return to borrowings and short selling restrictions. Brennan (1993), Karceski (1993), Falkenstein (2009), Blitz et al. (2013), Baker et al. (2012) show the existence of agency problem and decentralized investing approach. The borrowing restrictions and short selling constraints make institutional investors ignore low risk, high positive alpha stocks. Agency problems associated with portfolio construction motivate fund manager to increase their investments in high-risk stocks. This in turn enhances their personal compensation structure. It also makes the fund managers care more about out-performing in the bull market rather than under-performing in the bear market. It results in an increase in demand for high beta stocks which reduces the required rate of returns. Moreover, behavioural biases such as preference for lotteries, over confidence and representativeness motivate investors to demand high-risk stocks. This leads to increase in price for high-risk stocks.

Different studies have used different risk measures to explain the low-risk anomaly. Clarke, De Silva and Thorley (2010) constructed volatility-minus-stable (VMS) factor on the basis of idiosyncratic volatility. After controlling for size effect, VMS is able to explain the cross section of security returns. Frazzini et al. (2014) extend the scope of beta arbitrage by constructing Betting against Beta (BAB) factor. BAB portfolios across several asset classes and markets give higher returns. Garcia-Feijoo, Kochard, Sullivan, and Wang (2015) constructed the alternative (Alt- BAB) factor to further extend the scope of beta arbitrage.

In the Indian market, Agarwalla, et al. (2014) studied the returns of BAB (betting against beta) factor. They study found that BAB factor earns significant positive returns. Joshipura and Joshipura (2016, 2017) conducted a robust test and found that low volatility and low beta stocks earned higher returns than high volatility and high beta stock respectively as well as beat the benchmark market portfolio even after controlling for size, value and momentum factors.

Thus the literature in India as well as abroad provide evidence of the low-risk anomaly. The present study intends to further explore these findings. Data comprises of National Stock Exchange (NSE) listed stocks from January 2001 to June 2016 bifurcated into large cap, mid cap and small cap size buckets. It studies returns to volatility, idiosyncratic volatility and CAPM beta sorted portfolios.

The paper is organized as follows. Section I discusses data and methodology. Section II discusses results. Section III discusses the limitations and future scope of the paper. Section IV provides the conclusion to the paper.

2. Data and Methodology

According to World Federation of Exchanges (WFE), in 2015, the National Stock Exchange (NSE) was the leading stock exchange in India and the fourth largest in the world by equity trading volume. NSE India has a market capitalization of $1.87 trillion[1] in 2016-17. It has an average daily turnover of $3,185.5 million. The number of companies listed on NSE is 1,808 in 2015-16. NSE holds a leadership position across asset classes in the Indian and global exchange sectors. This demonstrates the robustness and liquidity of the exchange. The study includes data of all past and present stock constituents of NSE India. The period of study is from January 2001 to June 2016. We collected data from Capitaline database.

[1] $1 =Rs 64

We collected monthly data on stock prices[2], volume, market capitalization and earning to price.

The total number of stocks vary from period to period due to listing / de-listing of stocks on the exchange. This universe consisted of approximately 1,000 stocks, on average.

We collected Fama-French (1992) and Carhart (1997) momentum factors and risk free rate for the Indian Stock Markets from the IIM Ahmedabad data library.
We calculated the monthly log-return of stocks, volatility, idiosyncratic risk and CAPM beta for all stocks. We calculated the risk measures for each month using past 36 months excess log return of stocks. To separate the stocks into various size buckets, we first sorted the stocks in a particular month on the basis of its market capitalization. We then cumulated 75% of the total market capitalization in the large cap bucket. Companies falling in the next 20% of the total market capitalization were included in the mid cap bucket. The small cap bucket consisted of companies falling in the remaining 5% of the total market capitalization. We did this on a month-on-month basis. These were the breakpoints to allot stocks to the large cap, mid cap and small cap size buckets.

We calculated the stock returns and the three risk measures for 150 months in monthly iteration from January 2004 to June 2016. We eliminated from the sample any company with less than 12 monthly returns. Also, we eliminated companies that did not have a return in the month following the portfolio construction month (37th month). On monthly basis, we constructed equally weighted quintile portfolios from January 2004 onwards. We sorted stocks on volatility to construct low to high volatility portfolios. We repeated the same to form idiosyncratic volatility and CAPM beta sorted portfolios.

P1 quintile portfolio of every iteration of every market cap size bucket as well for every risk measure consists of low-risk stocks. Similarly, P5 quintile portfolio consists of highest risk stocks. We calculated monthly excess returns for the month following portfolio construction (37th month).

For the resulting time series, we calculated average annualized equally weighted excess returns, the standard deviation of returns, Sharpe ratio, CAPM alpha and ex-post beta. We considered equally weighted entire NSE listed equity stocks as proxy to market portfolio (EWI) on similar lines Blitz et al. (2007)

We used the three-factor and four-factor Fama-French-Carhart regression[3] to test the robustness of the results and the strength of low risk investing strategy. Also, it helped to separate the effect of low risk investing from other effects. We used market capitalization to measure size for calculation of SMB (small-minus-big) factor. Earnings-to-price was used for calculation of VMG (value-minus-growth) factor. We calculated past 12-months total returns minus 1-month returns to know the WML (winner-minus-loser) factor returns. In case of Fama-French Model, we regressed the returns of portfolios against market returns, SMB and VMG. In case of Fama-French-Carhart Model, we regressed the returns of the portfolios against market returns, SMB, VMG and WML. It controlled for any influence of these factors on the returns.

[2] All stock price data is adjusted for corporate action- Section I Data and Methodology

[3] Risk free rate and Fama-French and momentum factors data has been taken from IIMA Data Library- Section I Data and Methodology

Using the following classic one-factor regression, we calculated CAPM alpha with equally weighted Entire NSE market (EWI) as a proxy for market:

$$Rp,t\text{-}Rf,t= \alpha p+ \beta p,m\ (Rm,t\text{-}Rf,t)+\varepsilon p,t \qquad (1)$$

where Rp,t, Rf,t , Rm,t and Ɛp,t are the return on the portfolio p, risk-free rate, the return of the market portfolio and idiosyncratic volatility respectively in time t. The alpha of the portfolio is represented by αp.

The Fama-French 3 factor and Fama-French-Carhart 4 factor analysis is conducted by adding SMB, VMG and WML factors to the above equation 1.

$$Rp,t\text{-}Rf,t= \alpha p+\beta p,m\ (Rm,t\text{-}Rf,t)+ \beta p,smb{*}RSMB +\beta p,vmg{*}RVMG+\varepsilon p,t \qquad (2)$$

$$Rp,t\text{-}Rf,t= \alpha p+\beta p,m\ (Rm,t\text{-}Rf,t)+ \beta p,smb{*}RSMB +\beta p,vmg{*}RVMG+ \beta p,wml{*}RWML+\varepsilon p,t \qquad (3)$$

where RSMB, RVGM and RWML represent the return on size, value and momentum factors respectively and βsmb, βvmg and βwml represent betas of the portfolio of size, value and momentum factors of the study respectively.

3. Main Results

3.1 Results of TVOL and IVOL sorted portfolios

Panel A of Table I exhibits results of portfolios of large cap stocks sorted on volatility (TVOL). The excess return for low volatility quintile portfolio P1 is higher (8.28%) as compared to P5 (-15.28%) and market portfolio (-0.59%). There is a monotonic increase in the standard deviation from P1 (18.89%) to P5 (41.86%). The Sharpe ratio reduces from P1 (0.44) to P5 (-0.37) and it is also negative (-0.02) for the equally weighted market portfolio (EWI). The ex-post beta for P1 is the lowest (0.61). The CAPM alpha for P1 is the highest (8.67%) as well as economically and statistically significant. The differential gain by investing in low volatility portfolio and shorting high volatility portfolio (long-short strategy) is 23.56%. This is an exceptionally good return. The results show very clearly that there is a negative relationship between volatility and risk adjusted returns.

Panel B, Panel C and Panel D of Table I exhibits the above-mentioned results for mid cap, small cap, and entire NSE portfolios respectively sorted on volatility. These tables also show similar results as for large cap stock portfolios. The excess returns are diminishing, the standard deviation is increasing, the Sharpe ratio is decreasing, the ex-post beta is increasing and the CAPM alpha is decreasing from P1 to P5 in mid cap, small cap as well as EWI portfolios. The only exception in Table I Panel B is P3. Though the excess returns and alpha of P3 is greater than P2, it has a higher risk (measured by standard deviation and ex-post beta of the portfolio).

We observe a similar trend of returns from IVOL quintile portfolios as of TVOL quintile portfolios. The returns to low IVOL portfolio are economically and statistically significant though the intensity of the returns is different than TVOL portfolio.

Table I: Quintile portfolios based on historical volatility (Annualized Results) for Large Cap, Mid Cap, Small Cap and Entire NSE universe

	P1	P2	P3	P4	P5	P1-P5	EWI
Panel A: Historical Volatility sorted Large Cap Portfolios							
Excess Returns	8.28%	1.97%	1.50%	0.25%	-15.28%	23.56%	-0.59%
Std. Deviation	18.89%	23.38%	29.15%	31.48%	41.86%	31.30%	27.05%
Sharpe Ratio	0.44	0.08	0.05	0.01	-0.37		-0.02
Ex-post beta	0.61	0.82	1.03	1.12	1.45	-0.84	
Alpha	8.64%	2.45%	2.11%	0.91%	-14.42%	23.06%	
t-value	3.24	1.11	0.86	0.36	-3.48	3.79	
Panel B: Historical Volatility sorted Mid Cap Portfolios							
Excess Returns	7.03%	2.10%	2.89%	-2.00%	-12.97%	20.00%	-0.58%
Std. Deviation	20.79%	28.26%	30.69%	35.86%	43.11%	26.23%	31.00%
Sharpe Ratio	0.34	0.07	0.09	-0.06	-0.30		-0.02
Beta	0.64	0.89	0.97	1.14	1.36	-0.72	
Alpha	7.40%	2.62%	3.46%	-1.33%	-12.18%	19.58%	
t-value	4.07	1.68	2.13	-0.73	-4.72	5.03	
Panel C: Historical Volatility sorted Small Cap Portfolios							
Excess Returns	4.64%	-0.74%	-1.99%	-8.15%	-18.65%	23.29%	-5.01%
Std. Deviation	29.56%	35.55%	39.99%	42.31%	47.00%	21.80%	38.43%
Sharpe Ratio	0.16	-0.02	-0.05	-0.19	-0.40		-0.13
Beta	0.76	0.92	1.03	1.09	1.20	-0.44	
Alpha	8.43%	3.84%	3.19%	-2.67%	-12.64%	21.06%	
t-value	5.58	2.64	2.63	-2.01	-4.93	5.46	
Panel D: Historical Volatility sorted Entire NSE Portfolios							
Excess Returns	4.79%	1.83%	-1.42%	-6.16%	-16.94%	21.73%	-3.57%
Std. Deviation	24.55%	32.07%	36.22%	40.53%	45.57%	25.19%	35.29%
Sharpe Ratio	0.20	0.06	-0.04	-0.15	-0.37		-0.10
Beta	0.68	0.90	1.02	1.14	1.26	-0.59	
Alpha	7.20%	5.05%	2.22%	-2.08%	-12.42%	19.62%	
t-value	4.26	3.93	1.89	-1.72	-4.68	4.86	

Table I reports univariate analysis for the resultant time series of volatility sorted quintile portfolios constructed for large cap, mid cap, small cap and entire NSE universe in Panel A, B, C and D respectively. Each Panel reports annualised excess returns, standard deviation, Sharpe ratio, ex-post beta and CAPM style alpha with their t-value.

3.2 Results of Beta sorted portfolio

The results of ex-ante beta sorted portfolios are a bit different. The excess return for low beta large cap quintile portfolio P1 (3.36%) is marginally lower by 1.47% than P2 (4.83%) portfolio. Also, the excess return of low beta mid cap quintile portfolio P1 (3.92%) is marginally lower by 0.17% than P2 (4.09%) portfolio.

But the excess returns of the highest beta portfolio P5 (-14.34%) of large cap, mid cap (-8.51%) and the entire universe market portfolio (-0.59%) are lower than P1. The standard deviation is increasing monotonically from P1 to P5. The Sharpe ratio reduces from P1 to P5 but increases marginally in P2 (0.20) from P1 (0.17). It is also negative (-0.02) for the equally weighted market portfolio (EWI). The ex-post beta is increasing from P1 to P5. The CAPM alpha is higher and statistically significant for P2 and P3 as compared to P1 portfolios.

We observe in Table II that the P1 of beta sorted small cap stocks portfolio deliver negative excess returns. The excess returns from P2 and P3 are less negative than P1 though risk increases from P1 to P5.

Table II: Excess Returns of various portfolios sorted on different risk measures (Fig.in %)

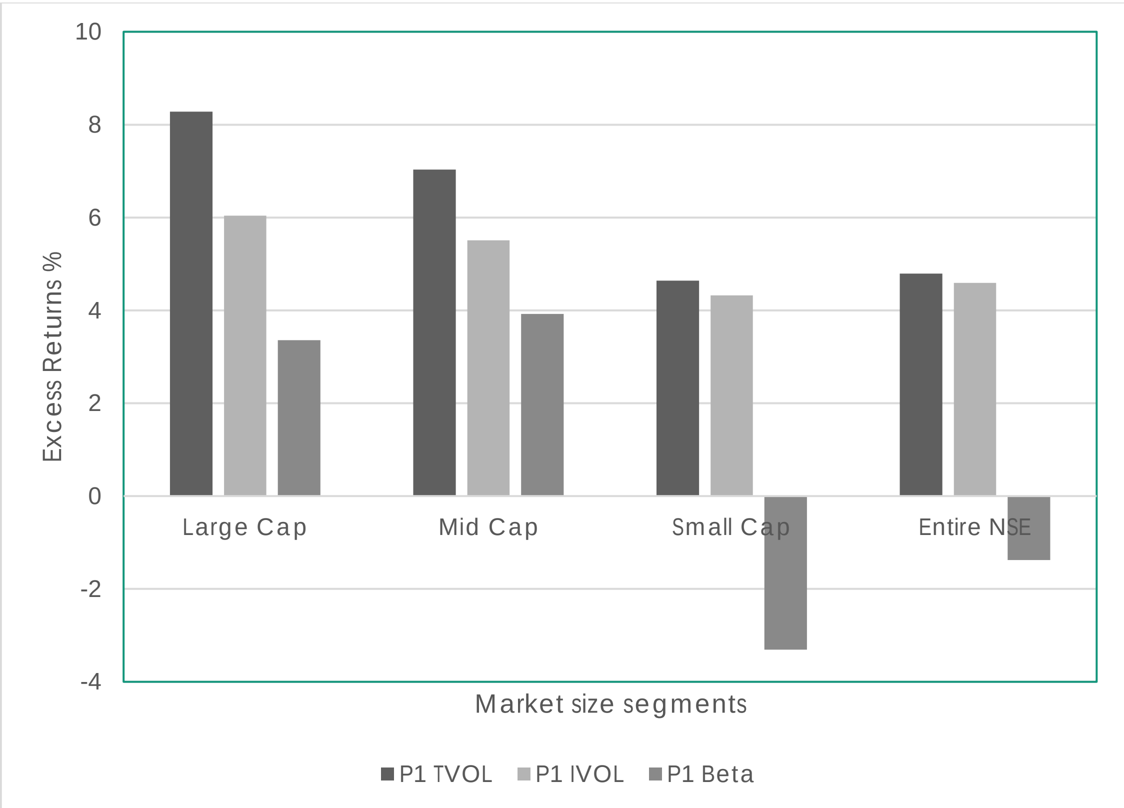
	Volatility (TVOL)				Idiosyncratic Volatility (IVOL)				Ex-ante Beta (β)			
	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE
P1	8.28	7.03	4.64	4.79	6.04	5.51	4.32	4.59	3.36	3.92	-3.31	-1.38
P2	1.97	2.10	-0.74	1.83	4.39	5.09	0.15	1.31	4.83	4.09	-1.68	1.46
P3	1.50	2.89	-1.99	-1.42	-2.22	-1.36	-4.64	-2.45	3.12	1.04	-0.73	-1.18
P4	0.25	-2.00	-8.15	-6.16	-0.12	-0.30	-6.35	-4.09	-0.29	-3.53	-6.0	-4.44
P5	-15.28	-12.97	-18.65	-16.94	-11.38	-11.91	-18.41	-17.25	-14.34	-8.51	-13.26	-12.35
P1-P5	23.56	20.00	23.29	21.73	17.42	17.41	22.73	21.83	17.70	12.44	9.94	10.97

Though the excess return of P1 is negative, it is less negative than P5 of beta sorted small cap portfolio. The same stands true for P1 of entire universe portfolio sorted by beta. The alpha of beta sorted P1 is less positive than P2 and P3 but it is negative for P5.

3.3 Other Results

As seen in Fig.1, volatility sorted large cap stocks earn the highest excess returns. The beta sorted small cap portfolio earn the least excess returns. The P1 of TVOL sorted large cap stocks give higher returns than P1 of IVOL or Beta sorted large cap stocks. The same stands true for mid cap, small cap and the entire universe market portfolio. The P5 of TVOL sorted small cap stocks earn highest negative excess returns, followed by IVOL and Beta.

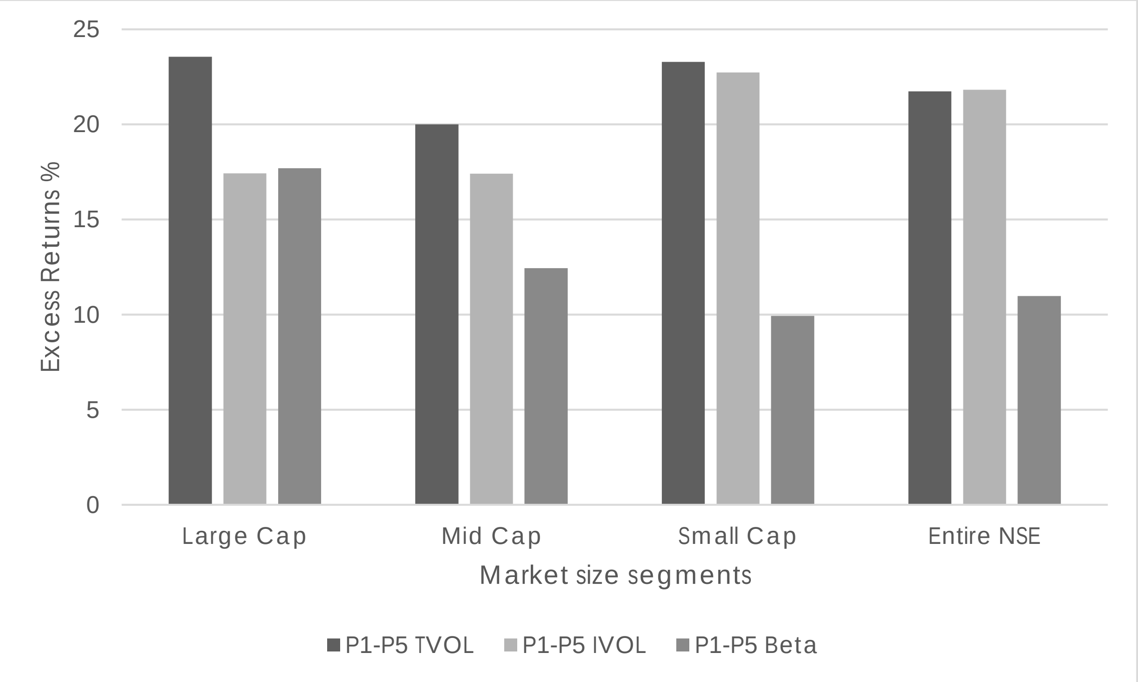
Fig.1: Various market sizes excess returns of lowest risk portfolio P1



3.4 Results of Long-Short Strategy

As observed in Fig. 2, the long- short strategy portfolios of all market size as well as risk measures deliver positive excess returns. The CAPM alpha is economically and statistically significant. The TVOL sorted large cap portfolio earn the highest excess returns. Whereas the Beta sorted small cap portfolio earn the least excess returns. The ex-post betas of this strategy in all market size bucket and risk measures are negative. Negative beta investment strategy indicates investment to hedge risk. This might not be preferable to the investment community. Also to successfully implement the long-short strategy requires leverage in investment which again might not be accepted by the mandates given to the investment houses. So though this strategy delivers high excess returns with zero risk, it might be rarely implementable.

Fig. 2: Various market sizes excess returns of P1- P5



3.5 Discussion of the test of robustness of low risk anomaly

Table III Panel A, B, C and D report single-factor, 3-factor and 4-factor alphas with their t-values of volatility sorted quintile portfolios of various market size buckets as well as entire NSE market.

The 3-factor alpha controls for size and value whereas for 4-factor alpha controls for size, value and momentum. The results show that P1 portfolios of all market sizes and the entire universe market have economically and statistically significant positive alphas. The alphas for P5 portfolios are negative and statistically significant. This helps us to understand that the low risk investing strategy is independent of size, value and momentum factors in the Indian stock market. Even the long –short strategy for all market size buckets have economically and statistically significant positive alphas. An exception to the trend is Table III Panel B P3 (mid cap size bucket). P3 gives better and significant alpha as compared to P2.

We observe similar results for idiosyncratic volatility sorted portfolios of all market size.

But for portfolios sorted on ex-ante beta, we do not observe the same trend. CAPM alpha of P2 portfolios of large cap, mid cap and the entire market universe is greater, positive and statistically significant than the alpha of P1 portfolios. P3 portfolios of these three market segments also have higher alphas than P1 but they are statistically insignificant. The alphas for P5 portfolios are negative and statistically significant. P3 of Beta sorted small cap portfolios have the highest alpha followed by P2 and they are even statistically significant whereas P1 alphas are small and insignificant.

We infer from above revelations that value, size and momentum affect the statistical significance of the low-risk investment strategy. In most of the result, the three- and four-factor alphas are greater than the single factor alpha. This supports the robustness of the low-risk investment strategy. We can devise a better investment strategy by controlling these factors. By doing so, we can enhance returns of the portfolio. So, we conducted further analysis of extreme portfolios.

Table III: CAPM Alpha, Three Factor (Fama-French) alpha and Four Factor (Fama-French-Carhart) alpha for historical Volatility sorted Quintile Portfolios of Large Cap, Mid Cap, Small Cap and Entire NSE universe

	P1	P2	P3	P4	P5	P1-P5
Panel A: Historical Volatility sorted Large Cap Portfolios						
CAPM style Alpha	8.64%	2.45%	2.11%	0.91%	-14.42%	23.06%
t-value	3.24	1.11	0.86	0.36	-3.48	3.79
3 factor alpha	9.29%	2.76%	2.73%	1.38%	-16.60%	25.89%
t-value	3.49	1.25	1.11	0.55	-4.18	4.39
4 factor alpha	6.60%	1.79%	2.28%	2.14%	-13.16%	19.76%
t-value	2.72	0.81	0.91	0.85	-3.51	3.69
Panel B: Historical Volatility sorted Mid Cap Portfolios						
CAPM style Alpha	7.40%	2.62%	3.46%	-1.33%	-12.18%	19.58%
t-value	4.07	1.68	2.13	-0.73	-4.72	5.03
3 factor alpha	7.14%	2.81%	3.49%	-1.07%	-12.42%	19.55%
t-value	3.92	1.82	2.11	-0.58	-4.81	5.03
4 factor alpha	6.44%	1.56%	3.91%	-1.32%	-10.59%	17.03%
t-value	3.53	1.06	2.34	-0.71	-4.26	4.51
Panel C: Historical Volatility sorted Small Cap Portfolios						
CAPM style Alpha	8.43%	3.84%	3.19%	-2.67%	-12.64%	21.06%
t-value	5.58	2.64	2.63	-2.01	-4.93	5.46
3 factor alpha	9.88%	5.25%	3.01%	-2.61%	-15.38%	25.26%
t-value	7.09	3.85	2.42	-1.93	-6.57	7.24
4 factor alpha	9.69%	5.17%	3.11%	-2.51%	-15.32%	25.02%
t-value	6.89	3.74	2.47	-1.84	-6.46	7.08
Panel D: Historical Volatility sorted Entire NSE Portfolios						
CAPM style Alpha	7.20%	5.05%	2.22%	-2.08%	-12.42%	19.62%
t-value	4.26	3.93	1.89	-1.72	-4.68	4.86
3 factor alpha	9.26%	6.68%	2.85%	-3.20%	-15.65%	24.90%
t-value	6.45	6.20	2.45	-2.84	-6.90	7.49
4 factor alpha	8.50%	6.63%	2.96%	-2.85%	-15.29%	23.79%
t-value	6.09	6.06	2.51	-2.53	-6.67	-6.67

Table III reports univariate and multivariate analysis for the resultant time series of volatility sorted quintile portfolios constructed for large cap, mid cap, small cap and entire NSE universe in Panel A, B, C and D respectively. Each Panel reports annualised CAPM style alpha with their t-value, three factor (Fama-French) and four factor (Fama-French-Carhart) alpha with corresponding t value.

Table IV reports the regression coefficients of P1 and P5 portfolios of Fama- French 3 factor regression. The FF alphas of all portfolios are significant other than P1 beta sorted portfolios. As we conducted the analysis for various market size buckets exclusively, we expected the results on size coefficient to be negligible. This happened to be true.

Table IV: Three Factor (Fama-French) Regression Coefficient Analysis for Large Cap, Mid Cap, Small Cap and Entire NSE universe portfolios sorted on Volatility, Idiosyncratic Volatility and Ex-ante Beta

	P1				P5			
	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE
Risk Measure –Volatility (Monthly data)								
FF Alpha	0.77%	0.59%	0.82%	0.77%	-1.38%	-1.03%	-1.28%	-1.30%
t-value	3.49	3.92	7.09	6.45	-4.18	-4.81	-6.57	-6.90
EWP	0.63%	0.64%	0.81%	0.75%	1.40%	1.34%	1.10%	1.14%
t-value	20.79	33.30	56.99	50.21	31.01	49.57	46.01	48.38
SMB	0.00%	0.08%	-0.01%	-0.08%	0.16%	-0.07%	0.06%	0.13%
t-value	-0.01	2.25	-0.49	-2.78	1.95	-1.44	1.33	2.86
VMG	-0.08%	-0.03%	-0.14%	-0.16%	0.14%	-0.09%	0.23%	0.24%
t-value	-1.91	-1.16	-5.70	-6.53	2.30	2.15	5.68	6.39
Risk Measure Idiosyncratic Risk (Monthly data)								
FF Alpha	0.62%	0.49%	0.83%	0.81%	-1.03%	-0.96%	-1.32%	-1.39%
t-value	3.46	3.89	6.84	7.38	-3.33	-5.26	-6.77	-7.43
EWP	0.75%	0.73%	0.86%	0.80%	1.22%	1.24%	1.04%	1.07%
t-value	31.04	45.63	57.56	58.80	28.69	53.89	43.54	45.69
SMB	-0.08%	-0.02%	-0.07%	-0.18%	0.10%	0.02%	0.14%	0.22%
t-value	-1.93	-0.77	-2.22	-6.80	1.32	0.39	2.90	4.73
VMG	-0.05%	0.02%	-0.12%	-0.13%	0.14%	0.03%	0.21%	0.24%
t-value	-1.34	0.94	-4.69	-5.88	2.38	0.97	5.24	6.29
Risk Measure – Beta (Monthly data)								
FF Alpha	0.34%	0.32%	0.05%	0.10%	-1.32%	-0.64%	-0.63%	-0.74%
t-value	1.23	1.86	0.37	0.73	-3.81	-2.68	-3.54	-4.03
EWP	0.63%	0.66%	0.80%	0.75%	1.38%	1.35%	1.19%	1.22%
t-value	16.90	29.89	47.61	43.32	29.08	45.22	54.32	52.85
SMB	0.07%	0.13%	0.10%	0.09%	0.17%	-0.18%	-0.12%	-0.07%
t-value	1.13	2.98	2.97	2.66	2.01	-3.15	-2.76	-1.56
VMG	-0.10%	-0.05%	-0.07%	0.06%	0.16%	0.14%	0.14%	0.17%
t-value	-1.92	-1.45	-2.41	-2.27	2.37	2.99	3.68	4.55

Table IV reports Fama-French Style regression coefficient of top and bottom quintile volatility, idiosyncratic volatility and beta portfolios with corresponding t value.

We observe that most of P1 consist of big stocks than small stocks. P5 consists of more small stocks than big stocks. The VMG factor in P1 has negative coefficients. It signifies that the portfolios consist of more growth stocks than value stocks. While the same does not stand true for P5. This explains that the low-risk effect is independent of small stock and value factor effect.

Table V lists the regression coefficients of P1 and P5 portfolios of Fama-French-Carhart 4 factor regression. The FF alphas of all portfolios are significant other than beta sorted low-risk portfolios. Additional factor added here is the momentum factor. It can be clearly observed that the P1 results are statistically significant for all market size segments. They consist of growth and winner stocks. While P5 consist of value and loser stocks.

So we can observe that positive risk-return relation is not holding true within the asset class though it is valid across asset classes. And such anomalous relationship is likely to prevail as long as market friction and behavioural biases continue to affect investment decision making.

Table V: Four Factor (Fama-French-Carhart) Style Regression Coefficient Analysis for Large Cap, Mid Cap, Small Cap and Entire NSE universe portfolios sorted on Volatility, Idiosyncratic Volatility and Ex-ante Beta

	P1				P5			
	Large Cap	Mid Cap	Small Cap	Entire NSE	Large Cap	Mid Cap	Small Cap	Entire NSE
Risk Measure –Volatility (Monthly data)								
FF Alpha	0.55%	0.54%	0.81%	0.71%	-1.10%	-0.88%	-1.28%	-1.27%
t-value	2.72	3.53	6.89	6.09	-3.51	-4.26	-6.46	-6.67
EWP	0.67%	0.65%	0.82%	0.77%	1.35%	1.31%	1.10%	1.14%
t-value	23.92	32.70	53.86	50.36	31.19	48.30	43.03	45.17
SMB	0.01%	0.08%	-0.02%	-0.09%	0.15%	-0.07%	0.07%	0.14%
t-value	0.14	2.21	-0.60	-3.20	1.97	-1.37	1.34	2.94
VMG	-0.06%	-0.03%	-0.14%	-0.16%	0.12%	0.08%	0.23%	0.24%
t-value	-1.66	-1.08	-5.74	-6.86	2.09	2.09	5.67	6.41
WML	0.19%	0.05%	0.02%	0.07%	-0.24%	-0.14%	-0.01%	-0.03%
t-value	6.00	2.19	0.95	3.61	-4.98	-4.18	-0.19	-1.02
Risk Measure Idiosyncratic Risk (Monthly data)								
FF Alpha	0.55%	0.52%	0.86%	0.80%	-0.96%	-0.95%	-1.35%	-1.43%
t-value	3.08	4.01	6.99	7.22	-3.04	-5.08	-6.90	-7.56
EWP	0.76%	0.72%	0.85%	0.80%	1.20%	1.24%	1.05%	1.08%
t-value	30.84	42.98	53.78	55.27	27.56	50.84	41.47	43.53
SMB	-0.08%	-0.02%	-0.06%	-0.18%	0.10%	0.02%	0.13%	0.21%
t-value	-1.90	-0.73	-2.05	-6.78	1.29	0.41	2.74	4.61
VMG	-0.04%	0.02%	-0.12%	-0.13%	0.13%	0.03%	0.21%	0.24%
t-value	-1.20	0.90	-4.64	-5.87	2.28	0.94	5.20	6.28
WML	0.05%	-0.02%	-0.03%	0.01%	-0.06%	-0.02%	0.04%	0.04%
t-value	1.93	-1.06	1.32	0.36	-1.32	-0.54	1.32	1.32
Risk Measure – Beta (Monthly data)								
FF Alpha	0.06%	0.15%	-0.04%	-0.02%	-0.97%	-0.44%	-0.55%	-0.62%
t-value	0.22	0.96	-0.29	0.12	-3.06	-1.96	-3.15	-3.56
EWP	0.68%	0.70%	0.83%	0.78%	1.31%	1.31%	1.16%	1.18%
t-value	19.82	33.74	49.96	47.79	29.94	44.89	51.79	51.31
SMB	0.08%	0.12%	0.08%	0.07%	0.16%	0.17%	-0.11%	-0.05%
t-value	1.42	3.13	2.61	2.42	2.09	-3.24	-2.45	-1.25
VMG	-0.08%	-0.04%	-0.07%	-0.07%	0.13%	0.13%	0.14%	0.17%
t-value	-1.67	-1.38	-2.80	-2.66	2.17	3.03	3.96	4.91
WML	0.24%	0.16%	0.10%	0.12%	-0.30%	-0.18%	-0.10%	-0.13%
t-value	6.12	6.19	4.99	6.21	-6.04	-5.16	-3.53	-4.45

Table V reports Fama-French-Carhart Style regression coefficient for top and bottom quintile volatility, idiosyncratic volatility and beta portfolios with corresponding t value.

4. Limitations and Potential Future Study

The study observed the returns to the low-risk anomaly in various market cap size buckets forming equally weighed portfolios. In future, the results can be tested using a different weighing scheme like value weighted scheme. This will further check the robustness of the results. Bivariate analysis can also be performed. The portfolios can be double sorted for growth and momentum. This will check the robustness of the results and provide strategic investing alternatives. Stock level analysis can be done to understand the characteristics of stocks which are picked up by low-risk investment strategy to deliver high returns.

5. Conclusion

To conclude, a low-risk investment delivers positive excess return. The CAPM alpha for low-risk portfolios is positive as well as economically and statistically significant. High-risk portfolios deliver negative excess returns. They have statistically significant negative alphas. Low-risk stocks portfolio returns exceed not only high-risk stocks portfolio but also equally weighted benchmark portfolio returns over a full cycle period. The returns of the low-risk stocks portfolio are independent of size as well as the risk measure.

The excess returns to TVOL are greater than IVOL or Beta. The excess returns to large cap portfolio are greater than mid cap and small cap portfolio. The low-risk anomaly is robust even after controlling for size, value and momentum factors. It is not a proxy for either of these factors. The low-risk portfolios majorly consist of large, growth and winner stocks rather than small, value or loser stocks. This clearly proves that the low-risk anomaly exists in the Indian equity market.

A strategy of investing in lowest volatility large cap stocks portfolio controlling value give high excess returns with economically and statistically significant alpha. Another strategy delivered by the study is investing in small cap growth stocks with the lowest volatility or idiosyncratic volatility. Though our universe consists of all stocks listed on NSE, the low-risk stock portfolio picked up large, growth and liquid stocks to deliver high excess returns. Also, low risk anomaly is a combination of systematic as well as unsystematic risk and not restricted to any one risk measure. The reasons that have been listed in the existing literature for the presence of low-risk anomaly apply to the Indian markets. While positive risk-return relation is valid across asset classes, the relation is not holding true within the asset class. Such anomalous relationship is likely to persist as long as market friction and behavioural biases continue to affect investment decision making.

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COMMODITY MARKET HETEROGENEITY AND CROSS-MARKET INTEGRATION

Michael Kunkler

Corresponding Author: Michael Kunkler, Relative Markets Limited, 4th Floor, 10 Lloyd's Avenue, London, UK, EC3N 3AJ. ☎ +44 (0) 7725 035669 ✉ michael.kunkler@relativemarkets.com

Abstract: We evaluate the recent levels of heterogeneity and cross-market integration for fluctuations in commodity futures returns for a post-financial-crisis data sample. We find that a single commodity-market risk factor explains 30.6% of the total variation in commodity futures returns. The commodity-market risk factor is significantly correlated with the dominant market-wide risk factors from other asset classes: +66.7% with a market risk factor for the US equity market; -74.2% with a US dollar risk factor for the FX market; and -27.8% with an interest-rate level risk factor for the US interest rate market. Thus, a part of the systematic variation in the commodity market is integrated with other asset classes.

Keywords: Commodity Market; Cross-Market Integration

1. Introduction

The commodity market offers diversification benefits from traditional asset classes such as stocks and bonds (for a review, see Skiadopoulos, 2013). However, to make informed decisions, investors need to measure the level of heterogeneity within the commodity market and the level of integration between the commodity market and other asset classes. The purpose of this paper is to measure both the level of heterogeneity and the level of cross-market integration of the commodity market for a post-financial-crisis data sample.

A strand of research has found that the commodity market is heterogeneous (Erb and Harvey, 2006; Kat and Oomen, 2007; Daskalaki et al., 2014). Historically, commodity futures returns have been shown to be largely uncorrelated with one another (Erb and Harvey, 2006). The heterogeneous structure of the commodity market makes it more difficult to identify systematic risk factors that may price common variation of commodity futures returns (Daskalaki et al., 2014). Furthermore, Skiadopoulos (2013) concludes that there are no common, or systematic, risk factors in commodity futures returns because, as an asset class, it is internally segmented. However, it has been suggested that recent increases in commodity return correlations are caused by investment in commodity indices (Tang and Xiong, 2012).

In contrast, another strand of research has proposed a number of common risk factors to explain fluctuations in commodity futures returns. Empirically, it has been reported that the average of the annualized individual commodity futures excess returns is approximately zero (Erb and Harvey, 2006). However, there is an observed equity-like average return of rebalanced equally weighted portfolios of commodity futures (Bodie and Rosansky, 1980; Erb and Harvey, 2006; and Gorton and Rouwenhorst, 2006). The rebalancing effect has directed research into long-short strategies in the commodity market.

Miffre (2016) provides an extensive review of long-short strategies in the commodity market, such as roll-yields, inventory levels, hedging pressure and past performance. Szymanowska et al. (2014) found three risk factors: one factor for spot premia, and two factors for term premia. Miffre and Fernandez-Perez (2015) find that commodity portfolios based on momentum, term structure or hedging pressure can achieve a lower correlation with the S&P 500 when compared to long-only commodity portfolios. More specifically, Basu and Miffre (2013) found a single risk factor based on hedging pressure. Additionally, Gorton et al. (2013) argue that fluctuations in commodity futures risk premiums depend on the level of physical inventories. Finally, Hong and Yogo (2012) use the growth rate in open interest as a predictor of commodity futures returns.

More generally, the commodity market appears to be segmented, rather than integrated, from other asset classes (Buyuksahin et al., 2010; Chong and Miffre, 2006; and Daskalaki et al., 2014). There is a reported small negative correlation between commodity returns against both equity and bond returns (Buyuksahin et al., 2010; Gorton and Rouwenhorst, 2006; and Greer, 2000). Skiadopoulos (2013) argues that the commodity market is segmented from both equity and bond markets. Similarly, Daskalaki, et al., (2014) argue that the commodity market is segmented from the equity market. In addition, Chong and Miffre (2006) provide historical evidence that commodity and equity markets have become more segmented.

In contrast, evidence for integration between the commodity market and other asset classes is less prevalent (Silvennoinen and Thorp, 2010; and Tang and Xiong, 2010). Silvennoinen and Thorp (2013) provide evidence of closer integration between commodity and financial markets based on increases in financial traders' open interest. The increase in open interest leads into the wider literature on the financialization of the commodity market (for a review, see Haase et al., 2016). The financialization of the commodity market results in commodity futures prices being determined by the aggregate risk appetite for financial assets (Tang and Xiong, 2012). Daskalaki and Skiadopoulos (2011) provide evidence that the financialization of commodity markets may reduce its diversification benefits from traditional asset classes.

Standard multifactor models are traditionally used to measure both the level of heterogeneity and the level of cross-market integration. Examples of different types of standard multifactor models applied to the commodity market can be found in Daskalaki et al. (2014).

Integrated multifactor models have been proposed to aggregate local multifactor models (Stefek, 2002; Anderson et al., 2005; Shepard, 2007). The central idea is to further decompose local systematic risk factors into global systematic and purely local contributions (Shepard, 2011). Not only does the integrated multifactor model allow for the inclusion of more risk factors, it also allows for the inclusion of specific cross-market correlations among individual local risk factors (Shepard, 2007). An integrated multifactor model may also be nested to add multiple levels of increasing resolution (Shepard, 2007).

We contribute to the literature by using a multilevel (or nested) integrated multifactor model, rather than the standard multifactor models, to measure both the level of heterogeneity within the commodity market and the level of cross-market integration between the commodity market and other asset classes. Furthermore, the multilevel integrated multifactor model allows for the inclusion of multiple futures for each commodity, interest rate, equity index and exchange rate.

At the commodity-market level, we find that a single commodity-market risk factor explains 30.6% of the total variation in commodity futures returns. At the less granular sector level, we find that six sector-level risk factors explain 60.7% of the total variation in commodity futures returns. Thus the commodity market has different levels of heterogeneity.

We also find that approximately 25% of the commodity market is integrated with, rather than segmented from, other asset classes. An implication of this finding is that the commodity market may not offer the level of diversification that is currently expected by investors.

2. Material and methods

2. 1. Multifactor models in each level

A multilevel integrated multifactor model is nested across many levels. At level *n* we define the *i*th linear multifactor model, in matrix notation, as:

$$\mathbf{r}_i^n = \mathbf{X}_i^n \, \mathbf{f}_i^n + \mathbf{u}_i^n \qquad i = 1, \ldots, M^n \tag{1}$$

where $\mathbf{r}_i^n$ is a N_i^n vector of security returns; $\mathbf{X}_i^n$ is a $N_i^n \times K_i^n$ matrix of risk factor sensitivities; $\mathbf{f}_i^n$ is a K_i^n vector of risk factors; and $\mathbf{u}_i^n$ is a N_i^n vector of security specific (idiosyncratic) returns. For levels beyond one (n>1), the *i*th vector of security returns consists of a selection of the risk factors from the previous level (n-1).

The total covariance matrix of the security returns for the *i*th linear multifactor model in level *n* can be decomposed in terms of the systematic risk factors by:

$$\mathbf{V}_i^n = \mathbf{X}_i^n \mathbf{F}_i^n \mathbf{X}_i'^n + \mathbf{\Delta}_i^n = \mathbf{\Sigma}_i^n + \mathbf{\Delta}_i^n \qquad i = 1, \ldots, M^n \tag{2}$$

where $\mathbf{V}_i^n$ is an $N_i^n \times N_i^n$ total covariance matrix of the security returns, $\mathbf{\Sigma}_i^n = \mathbf{X}_i^n \mathbf{F}_i^n \mathbf{X}_i'^n$ an $N_i^n \times N_i^n$ systematic covariance matrix of the security returns, $\mathbf{F}_i^n$ is a $K_i^n \times K_i^n$ covariance matrix of the systematic risk factors and $\mathbf{\Delta}_i^n$ is a positive definite $N_i^n \times N_i^n$ security specific covariance matrix of the security returns.

2. 2. Data

We use a post-financial-crisis data sample, where for all securities we use six years of monthly data from Bloomberg from 31st December 2009 to 31st December 2015. Our data sample is time independent from previous studies, with the exception of one year in common (2010) with Daskalaki, et al. (2014). We also use a larger sample of commodity futures than previous studies.

The commodity-market data sample consists of the three future contracts that are closest to maturity for 34 commodities: a total of 34 x 3 = 102 futures. Each commodity is grouped into one of five commodity sectors: energy, grains, livestock, metals and softs. These include six energy (kerosene, heating oil, crude oil, gas oil, gasoline, natural gas), ten grains (wheat, corn, crude palm oil, soybean oil, soybean, soybean meal, canola, oats, rough rice, red beans), three livestock (feeder cattle, live cattle, lean hogs), nine metals (gold, platinum, silver, palladium, copper, aluminium, lead, nickel, zinc) and six softs (cocoa, sugar, orange juice, coffee, cotton, lumber). All commodity futures are priced in US dollars.

The US interest rate market has three major sources of aggregate risk, which are represented by three named risk factors: level, steepness and curvature (Litterman and Scheinkman, 1991). The interest-rate level risk factor is the dominant risk factor. The interest-rate data sample consists of the three future contracts that are closest to maturity for four interest rates: 2-year, 5-year, 10-year and 30-year.

The equity-market data sample consists of the three future contracts that are closest to maturity for four US equity indices: S&P500, DJIA, Russell 1000 and NASDAQ. These four equity indices provide sufficient information to estimate a proxy for a US equity market risk factor.

The US dollar is usually classified as wholly systematic when constructing a set of (statistical) risk factors from a group of US dollar bilateral exchange rates (Lustig et al., 2011). The FX-market data sample consists of the three future contracts that are closest to maturity for the US dollar, which provide sufficient information to estimate a proxy for the US dollar risk factor in the FX market.

3. Results

3.1 Model structure

We use a four-level integrated multifactor model to capture the multiple levels of heterogeneity within the commodity market and the commodity market's relationship with other asset classes. We estimate the risk factors for each multifactor model in each level by principal components analysis.

Table 1 displays the overall structure of our proposed four-level integrated multifactor model. Although the overall structure exists on four levels, the structure for each asset class can exist on a different number of levels. For example, the structure of both the US interest rate market and the US equity market exist on three levels.

Table 1: Structure of the four-level multilevel integrated model

Commodity Market	Interest Rate Market	US Equity Market	FX Market
Commodity			
Sector	Interest rate	US equity index	
Commodity market	Interest rate market	US equity market	FX Market
Cross-market	Cross-market	Cross-market	Cross-market

When modelling term structures of futures prices by principal components analysis, the first risk factor usually represents a parallel shift for all futures prices and explains a significant proportion of fluctuations in the term structure (see Alexander, 2001).

Furthermore, in this paper, we use a single systematic risk factor for each risk model in level one. Including a second 'slope', or 'steepness', risk factor to measure common risk for either normal backwardation (downward sloping futures curve) or contango (upward sloping futures curve) remains a question for future research.

Figure 1 displays a graphical representation of the overall structure of the proposed four-level integrated multifactor model. To keep the figure readable, the level one risk models are excluded.

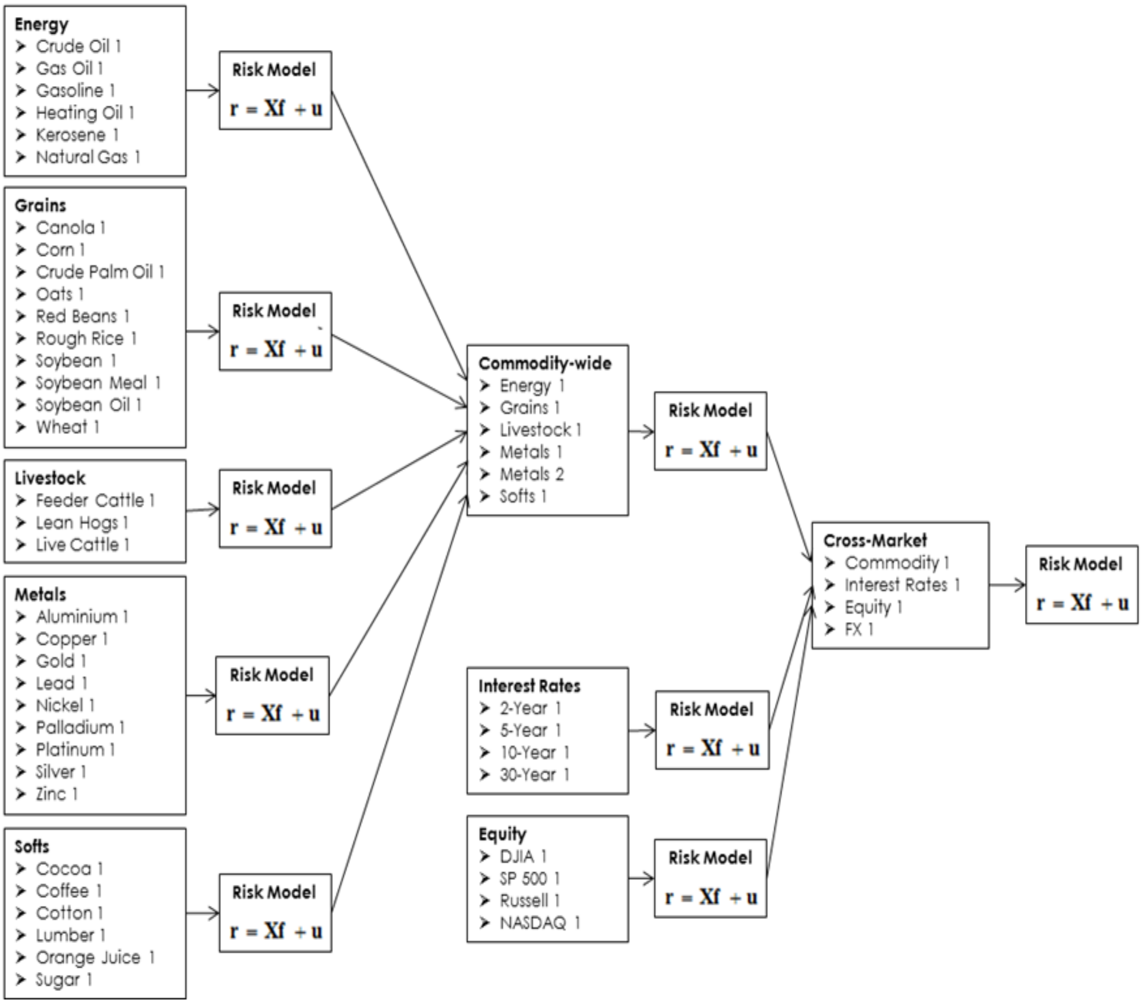

Figure 1: Structure of the four-level integrated multifactor model

In level one (n=1), the security returns are the returns of the three future contracts that are closest to maturity for each asset: commodity, interest rate, equity index, or exchange rate. A single future-level risk factor is produced for each level-one multifactor model.

For example, Table 2 displays the factor loadings for the crude oil risk factor resulting from a principal components analysis. The factor loadings are all positive and of a similar magnitude across the three future contracts. The single crude oil risk factor explains 98.2% of the total variation in the three crude oil futures returns, and represents a parallel shift for all crude oil futures prices.

Table 2: Factor loadings for the crude oil risk factor

Crude Oil Futures	Factor 1
Future 1	0.570
Future 2	0.585
Future 3	0.577

The FX multifactor model for level one uses the returns for the three US dollar future contracts to create a single FX-market risk factor. The structure of the FX market exists on only two levels. Therefore, the single FX-market risk factor directly enters the cross-market multifactor model (see Figure 1).

In level two (n=2), the level-one multifactor models are aggregated. For example, the commodity multifactor models from level one are aggregated within the five sector multifactor models in level two. Each sector-level multifactor model resulted in a single sector-level risk factor, except the metals multifactor model, which resulted in two sector-level risk factors.

Table 3 displays the factor loadings for the two risk factors associated with the metals sector. The first factor loadings (Factor 1) are all positive for all commodity-level risk factors. Thus the first risk factor represents a parallel shift for all commodities in the metals sector. The second factor loadings (Factor 2) are positive for the precious metals of gold at 0.605, silver at 0.528 and platinum at 0.281, and negative for the rest. Thus the second risk factor represents a precious metals versus base metals risk factor.

Table 3: Factor loadings for the two metals risk factors

Commodity Factors	Factor 1	Factor 2
Aluminium 1	0.356	-0.204
Copper 1	0.358	-0.206
Gold 1	0.256	0.605
Lead 1	0.337	-0.295
Nickel 1	0.340	-0.140
Palladium 1	0.339	-0.036
Platinum 1	0.352	0.281
Silver 1	0.293	0.528
Zinc 1	0.354	-0.291

The four interest rate multifactor models from level one are aggregated into a single interest-rate-market multifactor model, where a single market-wide risk factor is produced as a proxy for the level risk factor.

The four equity index multifactor models from level one are aggregated into a single US equity-market multifactor model, where a single market-wide risk factor is produced as a proxy for the equity-market risk factor for the US equity market.

In level three (n=3), the five sector multifactor models from level two are aggregated into a single commodity-market multifactor model, where a single market-wide risk factor is produced for the commodity market.

Table 4 displays the sector loadings associated with the single commodity-market risk factor. The risk factor loadings are large and positive for four out of the six sector risk factors: 0.493 for the energy sector (Energy 1); 0.465 for the grains sector (Grains 1), 0.521 for the first risk factor of the metals sector (Metals 1) and 0.517 for the softs sector (Softs 1). Thus the single commodity-market risk factor can be seen as a proxy for the commodity market. However, the livestock sector moves independently from all the other commodity sectors, with a very small factor loading of 0.043.

Finally, in level four (n=4), the four market-wide multifactor models (commodity market, US interest rate market, US equity market, and FX market) are aggregated into a single cross-market multifactor model. This model decomposes the market-wide risk factors into cross-market systematic and market-wide specific contributions.

Table 4: Factor loadings for the commodity-market risk factor

Sector Factors	Factor 1
Energy 1	0.493
Grains 1	0.465
Livestock 1	0.043
Metals 1	0.521
Metals 2	0.003
Softs 1	0.517

Table 5 displays the loadings associated with the single cross-market risk factor. The risk factor loadings are positive for both the commodity market risk factor at 0.566 and the equity market risk factor at 0.540, and are negative for both the interest rate market risk factor at -0.328 and the FX market risk factor at -0.529. The single cross-market risk factor explains 62.3% of the total variation in the underlying four market-wide risk factors. Therefore, there is a common cross-market risk factor across all asset classes.

Table 5: Factor loadings for the cross-market risk factor

Market Factors	Factor 1
Commodity 1	0.566
Interest Rates 1	-0.328
Equity 1	0.540
FX 1	-0.529

3.2 Commodity Market Analysis

The structure of the commodity market exists on four levels. The total covariance matrix for the security returns in level one $\mathbf{V}_i^1$ from (2) can be decomposed into each level by:

$$\mathbf{V}_i^1 = \mathbf{\Sigma}_i^4 + \mathbf{\Omega}_i^4 + \mathbf{\Omega}_i^3 + \mathbf{\Omega}_i^2 + \mathbf{\Delta}_i^1, \qquad i = 1,\ldots,M^1 \qquad (3)$$

where $\mathbf{\Sigma}_i^4$ is the level-four systematic cross-market covariance matrix; $\mathbf{\Omega}_i^4$, $\mathbf{\Omega}_i^3$, and $\mathbf{\Omega}_i^2$ are three factor specific covariance matrices for level four (commodity market), level three (sector) and level two (commodity), respectively; and $\mathbf{\Delta}_i^1$ is the security (futures) specific covariance matrix from (2).

The estimated multilevel integrated multifactor model is used to decompose the total variance for commodity futures returns using (3). Table 6 displays the percentage contribution to variance averaged within each of the five commodity sectors.

Table 6: Percentage contribution to variance for each commodity future returns averaged within each commodity sector, where each row sums to 100%

Sector	Count	Cross-Mkt Systematic	Com-Mkt Specific	Sector Specific	Commodity Specific	Future Specific
Energy	6	34.3%	8.7%	29.7%	25.4%	1.9%
Grains	10	22.8%	5.8%	25.6%	42.6%	3.3%
Livestock	3	0.2%	0.1%	63.5%	29.0%	7.2%
Metals	9	32.6%	8.3%	36.7%	22.2%	0.3%
Softs	6	17.2%	4.4%	11.5%	64.4%	2.5%
Average	**34**	**24.4%**	**6.2%**	**30.1%**	**36.8%**	**2.4%**

The cross-market (Cross-Mkt) systematic column represents the average percentage of the total variation in commodity futures returns that is explained by the single cross-market risk factor. The overall average of 24.4% demonstrates that about a quarter of the commodity market is integrated with other asset classes. The energy sector is the most integrated with 34.3%. In comparison, the livestock sector is the least integrated with 0.2%.

To measure the level of heterogeneity within the commodity market, we look at the amount explained by the commodity-market (Com-Mkt) systematic, which is found by adding the cross-market systematic plus the commodity-market specific columns. The commodity-market systematic represents the percentage of total variation in commodity futures returns that is explained by the single risk factor for the whole commodity market. The overall average of 30.6% (24.4% + 6.2%) demonstrates that approximately 70% of the commodity market is heterogeneous. The livestock sector is the most heterogeneous (least homogenous) with an average of 0.3% (0.2% + 0.1%). Conversely, the energy sector is the least heterogeneous (most homogenous) with an average of 43.0% (34.3% + 8.7%).

The livestock sector is segmented from other asset classes and moves independently from all the other commodity sectors. The livestock sector also has the highest explanation from the sector-specific risk factor at 63.5%.

It is noteworthy that the average of the future-specific percentage contributions to variance is very small at 2.4%. Thus the first risk factors in the level-one multifactor models explain a significant proportion of fluctuations in the futures term structures. The average future-specific percentage contribution to variance is largest for the livestock sector with 7.2%, which indicates the presence of seasonality. The average future-specific percentage contribution to variance is smallest for the metal sector with 0.3%, where seasonality is rarely present.

An alternative measure of the level of heterogeneity in the commodity market is to look at the amount explained by the sector systematic (sector risk factors), which is found by adding the cross-market systematic plus the commodity-market specific plus the sector specific columns. The sector systematic represents the percentage of total variation in commodity futures returns that is explained by the six sector-level risk factors. The overall average of 60.7% (24.4% + 6.2% + 30.1%) demonstrates that there is common structure at different levels of the commodity market.

3.3 Cross-market Analysis

Table 7 displays the correlation matrix for the market-wide risk factors. These include one commodity-market risk factor (Commodity 1), one US interest rate market risk factor (Interest Rates 1), one US equity market risk factor (Equity 1) and one FX market risk factor (FX 1).

Table 7: The correlation matrix for the market-wide risk factors. We denote by *, **, and * as showing sufficient evidence to reject the null hypothesis of zero correlation at the 10% level, the 5% level, and 1% level, respectively**

	Commodity 1	Interest Rates 1	Equity 1	FX 1
Commodity 1	**1.000**			
Interest Rates 1	**-0.278****	1.000		
Equity 1	**0.667*****	-0.409***	1.000	
FX 1	**-0.742*****	0.210*	-0.558***	1.000

The risk factor for the commodity market (Commodity 1), which explains 30.6% of the total variation in commodity futures returns, is significantly correlated with the risk factors from the other asset classes: +66.7% with the risk factor for the US equity market (Equity 1); -74.2% with the risk factor for the FX market (FX 1); and -27.8% with the risk factor for the US interest rate market (Interest Rates 1). Thus, a part of the commodity market appears to be significantly integrated with other asset classes.

4. Conclusion

Multilevel integrated multifactor models are capable of measuring the different levels of heterogeneity within the commodity market and of measuring the level of cross-market integration that the commodity market has with other asset classes.

We found that the commodity market is approximately 70% heterogeneous, with one commodity-market risk factor explaining 30.6% of the total variation in commodity futures returns. However, at the sector level, the commodity market is approximately 40% heterogeneous, with six sector-level risk factors explaining 60.7% of the total variation in commodity futures returns. These results indicate that there is common structure within the commodity market that exists at different levels.

We also found that approximately 25% of the commodity market is integrated with other asset classes. More specifically, there is a significant part of the systematic variation of the commodity market that is integrated with other asset classes. Therefore, the commodity market may not offer the level of diversification that is currently expected by investors. If investors choose to add commodities to their portfolios, they should be aware that they may be unintentionally increasing their exposure to other asset classes.

Further research is required to test the robustness of our results. For example, further research is required to investigate whether the observed level of integration in our post-financial-crisis data sample is present in previous periods.

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SHORT AND SWEET OR JUST SHORT?

THE READABILITY OF PRODUCT DISCLOSURE STATEMENTS

AARON GILBERT[1*], AYESHA SCOTT[2]

1. Auckland University of Technology & Auckland Centre for Financial Research, New Zealand
2. Auckland University of Technology

* Corresponding Author: Aaron Gilbert, Associate Professor, Department of Finance, Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand
☎ +64 (9) 921 9999 Ext.5617 ✉ agilbert@aut.ac.nz

Abstract: Given the importance of information in making informed financial decisions, it is vital that investors are able to understand the information provided to them. With this in mind, in 2013, New Zealand legislators replaced the existing disclosure documents with the Product Disclosure Statement ("PDS"). The change was in response to large and complex disclosure documents from providers of new or ongoing sales of financial products. PDS documents have a strictly enforced word limit and are meant to be written in plain English to allow "prudent but non-expert" investors access to the information they contain. We compare the readability of the old prospectus and investment statements (the disclosure documents legally required before 2013) with the new PDS for a sample of superannuation mutual funds (referred to in New Zealand as KiwiSaver funds). We find that while the documents are definitely shorter, there have been mixed improvements in the readability of the documents. The main improvements are a reduction in the amount of finance terminology used, while the language in PDSs compared to investment statements is actually more complex, likely driven by the word limit. As a result, while investors require less finance knowledge, they appear to require a higher level of general education to understand the documents, potentially putting the information out of reach of over half the general population.

Keywords: Readability, financial disclosure, KiwiSaver

1. Introduction

The creation of the Product Disclosure Statement (PDS) disclosure regime in New Zealand's Financial Markets Conduct Act 2013 was designed to overcome several weaknesses with prospectuses. Prospectuses and investment statements had become increasingly long and complex over time, and had transformed from documents providing information to investors into documents designed to limit potential liability. As a result, there is a widespread belief that investors stopped using prospectuses and investment statements to make financial decisions about investing in new products or issues. The PDSs are designed to be shorter (for managed investment products they are limited to 6,000 words or 12 pages) and issuers are encouraged to make them easier to read. This research examines whether the new documents are significantly easier to understand.

We consider the ease with which an investor can understand a document in two ways; language complexity and the amount of financial terminology an investor needs to know in order to understand the PDS. Readability is particularly important in the context of KiwiSaver as these are products that are sold to 'everyday' investors, and have been widely taken up by the New Zealand investing public.[1] KiwiSaver was introduced in New Zealand in 2007 as a defined contribution superannuation savings scheme to address the baby boomer retirement issue. The scheme was set up on an opt-out basis, where employees starting a job would be given a short period to opt-out, otherwise they were enrolled. Investors have a limited number of decisions that they need to make, specifically their contribution rate (3, 4 or 8%), the fund type (cash, conservative, moderate, balanced, growth or aggressive) and fund provider. Members who did not make a decision were auto-enrolled into a conservative fund run by a limited number of default providers. In total there are currently 25 providers (although this number has changed over time as a result of the entrance of new providers, mergers and closures), offering 144 different funds managing, as at Oct 2017, over NZ$40 billion. KiwiSaver offers an excellent opportunity to examine readability as it is a product sold to a wider audience than most investment products, making readability even more important given many participants lack of financial knowledge, and products are sold on a continual basis requiring updated disclosure documents from the same providers. This creates a nice sample for this natural experiment.

To look at whether the PDS documents are easier to read, we compare the last prepared prospectus and investment statement with the first PDS document for each fund manager. We use a range of metrics designed to measure the readability of the text and the amount of financial terminology contained in the document. We compare each of the measures for 21 fund providers for their publicly available prospectus and PDS, and a smaller sample of 18 funds who provided us with copies of their old investment statements, and test the statistical significance of the differences.

The results show that the PDS regime has resulted in a significant reduction in the amount of financial terminology that investors need to understand, from approximately 240 terms to 103 (the percentage of complex words is also lower for the average PDS, at 15.3% compared to 19.3% for the average prospectus). However, when compared with the investment statement, other readability measures suggest the PDS has resulted in less readable documents. While sentence lengths remain similar, the complexity of the language increased, and finance terms were used proportionally more frequently. Compared to the prospectus the results for language complexity are again mixed. On one hand, the language used is simpler, with a reduction in the number of large words. On the other hand, the length of the sentences has significantly increased, making them more complex and potentially harder to digest. Additionally, the increase in the length of the sentences outweighs the simplification of the language. Therefore, in general it appears that investors require a significantly higher level of education to understand the product disclosure statements than either the prospectus or investment

[1] While KiwiSaver has been sold to the public at large in New Zealand, the Financial Markets Conduct Act sets the target for the readability of PDS documents as "prudent but non expert" investors. While the legal formulation as to this level of investor is arguably higher than the general public, we have chosen to assess readability in relation to the wider public as this is the target market for KiwiSaver.

statement. Overall, the results suggest that there has been progress toward more accessible disclosures, but there is still considerable room for improvement.

2. Literature Review

The use of textual analysis and readability measures are a recent development in the field of finance, although they have an established history in other fields. Additionally, many of the studies to date have been restricted to considering annual reports, specifically the U.S.-based 10-K documents. For instance, Li (2008) considered the impact of annual report readability on firm performance using the Fog Index. The Fog Index is a function of word complexity and sentence length. Li finds that firms with lower earnings have higher Fog Index scores, which indicates that they are harder to read. Additionally, firms with better readability have higher earnings persistence. Biddle, Hilary and Verdi (2009) find that firms with higher readability have greater capital investment efficiency, while Guay, Samuels and Taylor (2015) find that firms with less readable annual reports try to overcome this by issuing more managerial forecasts. Lundholm, Rogo and Zhang (2014) find that foreign firms listing in the U.S. have more readable documents. They suggest foreign firms need to make their information clearer than domestic firms to attract investors.

Readability also impacts on the way investors behave in relation to firms. Miller (2010) finds that retail investors trade fewer shares in firms with less readable and larger annual reports, while Lawrence (2013) finds that small investors invest more in firms with more readable and shorter annual reports. Analysts are also impacted by the readability of annual reports. Lehavy, Li and Merkley (2011) find that firms with less readable annual reports attract more analysts, have higher analyst dispersion and lower earnings forecast accuracy. Additionally, the quartile with the worst readability have a Fog Index that requires a level of education greater than a Master’s degree to understand and therefore are considered unreadable.

Studies considering documents other than annual reports are less common. De Franco, Hope, Vyas and Zhou et al. (2015) consider the readability of analyst reports and find that more readable analyst reports result in increased stock trading volumes in the days immediately following the report’s release. They argue this is consistent with models that suggest investors will initiate trades when they have access to more precise information. Additionally, Cash and Tsai (2017) study the readability of credit card agreements. They find the average agreement is written to an 8th or 9th grade level, which is greater than the average American’s reading level. Additionally, more readable agreements are associated with lower annual percentage rates.

Studies related to offer documents have not tended to consider readability, although some studies have conducted textual analysis of IPO documents for equity issues. Hanley and Hoberg (2010) consider the informativeness of IPO disclosure documents. They split the information contained into standard and informative components by comparing the information contained in an IPO disclosure compared with prior IPO documents. They find that more informative IPO disclosures reduce the amount of underpricing, and can substitute for book-building processes. Loughran and McDonald (2013) consider the definitiveness of the language in the first SEC filing in the IPO process (the S-1 form). They find that weaker language, such as words like ‘may’ and ‘might’, especially in relation to the business strategy section, results in higher first day returns, increased likelihood of price revisions and more volatility.

The focus on U.S. annual reports has meant little research has considered disclosure documents designed for the sale or offer of new financial products, nor documents aimed at products other than equities. The literature has however shown that financial documents are generally pitched at a relatively high level, making them difficult to read by the vast majority of the general public. However, firms that try to write more readable documents appear to be rewarded with more investor interest, therefore readability is a desirable trait.

3. Methodology

We study the readability of disclosure documents using a number of metrics that have been applied previously to study the readability of financial documents. Loughlin and McDonald (2014) argue the complexity of language, commonly measured via measures such as the Fog Index, does not fully account for the complexity of understanding financial documents. We follow Loughlin and McDonald (2013) and measure the readability of KiwiSaver documents by looking at both the complexity of the language and the amount of financial jargon that is contained in the document. We employ the Loughran-McDonald master dictionary list, which provides the number of syllables for each word. We also consider the number of unique words as a percentage of the total dictionary of words used in a document. This measures the range of vocabulary required to understand a document.

To measure complexity of the language we apply the Fog Index. This is a widely-used measure of readability and has been applied in numerous fields of research. The Fog Index measures readability based on the percentage of complex words, defined as words of three syllables or more, and the average number of words per sentence. The formula is as follows:

$$FI = 0.4 * (WordsPerSentence + \%ComplexWords * 100) \quad (1)$$

The Fog index is a simple way of measuring one aspect of readability, although it has been criticised by some. For example, the measure doesn't take into account other aspects of readability such as active vs passive voice, the use of graphics to convey information or the way information is laid out or structured. Unfortunately, objective measures for these additional aspects do not currently exist.

As Loughlin and McDonald (2013) point out, another component of readability of financial documents is the amount of jargon and technical terms that a reader needs to comprehend in order to understand a document. We use Campbell Harvey's hypertext finance dictionary to create a dictionary of finance terms. As per Loughlin and McDonald (2013), we remove multiple word phrases and acronyms. The hypertext dictionary was developed within the U.S. context, therefore we add terms associated with KiwiSaver and New Zealand. We measure the amount of jargon in two ways. First, the unique number of financial terms contained in the document as a percentage of the total words and second, the percentage of finance terms in the document.

We collect the last prospectus and investment statement and the first product disclosure statement for each fund manager from the Disclose Register[2] provided by the New Zealand Companies Office. As these documents are in PDF format, we convert

2 https://disclose-register.companiesoffice.govt.nz/disclose

them to text files. As a result, we manually check the documents for accuracy, as figures and tables do not convert well. We also check for spelling, including differences between American and English spelling. We considered the body of the document to end prior to the application form, as the structure of the application forms would make them extremely problematic to analyse. Our resulting database contains all the words in each individual document, the number of times they occur, the number of syllables in the word and whether it is a finance term.

4. Results

4.1 Investment Statement vs. PDS

Investment statements were intended to act as a plain English version of the information contained within the prospectus, and to act as the primary disclosure document for investors. However, while the goal initially was to create a plain English document investors could read, they became more complicated and longer over time. As a result, the New Zealand regulator, the Financial Markets Authority, in June 2012 issued a guidance note entitled “Effective Disclosure” which put emphasis on improving disclosure in the investment statements. As investment statements were meant to be the disclosure document provided to investors, we initially compare investment statements to the product disclosure statements. However, as old copies of investment statements are not publicly available, we were only able to collect investment statements from 18 of the 21 fund managers who operated both before and after the change to PDSs (with the assistance of the KiwiSaver Industry Working Group). In Table 1 we compare the investment statement readability measures with the PDS results. We also calculate the difference between the two averages, and the statistical significance of the difference using a matched pair *t*-test.

The results are interesting, and offer a mixed view of the benefit of the PDS. We observe a significant reduction in the size of the documents as a result of the introduction of the PDS. PDS’s are on average less than a quarter of the length of investment statement based on words, and 1/6th the length based on sentences. Of note, we observe a large difference in the PDSs, between 3400 and 6500 words. Given the limited word count and mandatory text, it is notable that one fund manager managed to use just over half the word count. This may be due to relying more heavily on Other Material Information documents. Additionally, more complex fund providers, which run a number of funds covering multiple risk levels, are able to avoid duplicating tables by placing some of the PDS information into the regular fund updates, provided these are also given to investors alongside the PDS. These factors may account for the differences in length.

However, the language in the PDS is significantly more complex. The percentage of complex words is 5.3% higher in the PDS, which combined with an insignificant difference in the average sentence length, results in a 2.6 increase in the Fog Index. The average Fog index of 9.7 for investment statements suggests that people only need an early high school education to understand them, compared with the 12.35 for the PDS, which relates to an education level of the final year in high school. Currently only 1 in 2 students completes high school (in New Zealand, high school certification is Level 3 NCEA), suggesting the PDS is beyond the understanding of half of all secondary students. While the readability of the average PDS is lower than the average investment statement, the level of vocabulary required is much less. We see the percentage of unique words in the PDS is under half that of the investment statement. One caveat on the Fog index findings is an issue regarding how a sentence is determined. This is a known weakness of the Fog index and makes the Fog easiest to apply when dealing with traditionally formatted text documents, i.e. with lots of paragraphs. The PDS, and to a lesser degree the investment statements, include a lot of information in bullet pointed lists which can result in longer sentence lengths, but not necessarily in less readable text. We have done our best to treat bullet pointed lists consistently but they are a limitation to our findings.

Table 1: Investment Statement vs PDS Results

	Investment Statement			Product Disclosure Statements			
	Average	Minimum	Maximum	Average	Minimum	Maximum	Difference in Averages
Number Words	22720.72	10750	71434	5226.78	3469	6474	-17493.94***
Number Sentences	2045.83	545	3679	335.06	238	432	-1710.78***
Words Per Sentence	14.53	5.64	45.23	15.75	11.74	17.85	1.22
% Complex	9.83%	0.05%	14.74%	15.14%	13.80%	17.70%	5.31%***
Fog Index	9.74	6.99	18.37	12.35	10.50	13.91	2.61***
% Unique Finance Words	2.14%	0.23%	3.29%	1.04%	0.74%	1.26%	-1.10%***
% Doc Finance Words	8.01%	0.18%	13.72%	12.52%	10.60%	14.79%	4.51%***
% Dict	10.49%	1.26%	15.07%	7.62%	5.54%	9.23%	-2.87%***

Note: We examine the investment statement and product disclosure statements of 18 KiwiSaver providers where we could obtain both documents. *Number of Words* is defined as the total number of words in the document after excluding abbreviations, names and addresses. *Number of Sentences* is defined as the number of non-heading sentences in the document. *Words per Sentence* is defined as number of words in the document divided by the number of sentences. *% Complex* is defined as the number of words contained three or more syllables divided by the total number of words in the document. The number of syllables was sourced from the Loughlin-McDonald 2011 master dictionary. *Fog Index* is calculated as per equation 1. *% Unique Finance Words* is the number of unique words from the Campbell Harvey hypertext finance dictionary contained within the document as a percentage of the total number of words in the finance dictionary. The finance dictionary was amended to include terms related to NZ. *% Doc Finance Words* is defined as the sum of the number of times each word contained in the finance dictionary occurs divided by the total number of words in the document. *% Dict* is defined as the total number of unique words contained in the document as a percentage of the number of words in the master dictionary. Significance of the difference in averages was calculated using a matched pairs *t*-test. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

We also observe that the level of finance knowledge required to understand the PDS is lower. The percentage of unique finance terms in the PDS halves. However, the percentage of finance terms in the PDS is higher, 12.5% compared with 8%. In essence, the investment statement uses a wider range of finance terms, but overall uses finance terms less frequently. An interesting point to note is that most of the investment statements also contain a glossary of finance terms, something that has been left out of the PDS . This may actually improve the investors ability to access the information within the investment statement as plain English explanations are provided within the document, and do not require the reader to go further to find the meaning of terms. A glossary may be worth considering in future revisions to the PDS, although we have no empirical evidence on the value of the glossaries at this stage.

One way to interpret the mixed results regarding readability between the investment statement and the PDS is that fund providers are struggling to convey all the required information within the strict word limits mandated for the PDS. Some consequences of this may be greater use of complex language, where a longer and more complicated word can replace a several simple words, resulting in less readability. Similarly, it may also explain the greater frequency of finance terms, where finance terms can be shorter to use.

4.2 Prospectuses vs. PDS

Table 2 presents the results of the final prospectus prior to the change and the first PDS following the change, averaged over the 21 fund managers. The documents are considerably shorter. On average, KiwiSaver prospectuses were nearly 30,000 words and close to 3,000 sentences compared with just 5,200 words and 328 sentences for the PDS. Interestingly, there is quite a large range. The shortest prospectus was just over 16,000 words and the largest is over 62,000 words, close to four times longer than the shortest.

Table 2: Prospectuses vs. PDS

	Prospectuses			Product Disclosure Statements			
	Average	Minimum	Maximum	Average	Minimum	Maximum	Difference in Averages
Number Words	29208.81	16176	62447	5166	3469	6474	-24043***
Number Sentences	2976.86	1536	6208	327.95	238	432	-2649***
Words Per Sentence	9.77	8.13	10.70	15.92	11.74	18.91	6.16***
% Complex	19.28%	17.57%	21.07%	15.29%	13.80%	17.70%	-4.00%***
Fog Index	11.62	10.52	12.62	12.48	10.50	14.08	0.86***
% Unique Finance Words	2.61%	2.02%	3.70%	1.04%	0.74%	1.26%	-1.57%***
% Doc Finance Words	12.05%	9.82%	14.53%	12.49%	10.47%	14.79%	0.44%
% Dict	17.95%	14.77%	22.45%	7.63%	5.54%	9.23%	-10.32%***

Note: We examine the prospectus and product disclosure statements of 21 KiwiSaver providers who had both documents publicly available. *Number of Words* is defined as the total number of words in the document after excluding abbreviations, names and addresses. *Number of Sentences* is defined as the number of non-heading sentences in the document. *Words per Sentence* is defined as number of words in the document divided by the number of sentences. *% Complex* is defined as the number of words contained three or more syllables divided by the total number of words in the document. The number of syllables was sourced from the Loughlin-McDonald 2011 master dictionary. *Fog Index* is calculated as per equation 1. *% Unique Finance Words* is the number of unique words from the Campbell Harvey hypertext finance dictionary contained within the document as a percentage of the total number of words in the finance dictionary. The finance dictionary was amended to include terms related to NZ. *% Doc Finance Words* is defined as the sum of the number of times each word contained in the finance dictionary occurs divided by the total number of words in the document. *% Dict* is defined as the total number of unique words contained in the document as a percentage of the number of words in the master dictionary. Significance of the difference in averages was calculated using a matched pairs *t*-test. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

We see mixed evidence of improvement in the complexity of the language used. On one hand, the number of unique words more than halves while the percentage of complex words in the PDS is 4% less, going from 19% to 15%. Additionally, the minimum values for the number of unique words and percentage of complex words for the average prospectus are higher than the maximum for the average PDS. This suggests that an effort has been made to simplify the language used within the PDS text. However, the sentences have become longer in all cases, moving from an average of just under 10 words per sentence to nearly 16. As a result of the significant increase in words per sentence, we see an increase in the Fog Index from 11.62 to 12.48, an increase of 0.86. A possible interpretation is that readers require nearly a full year of additional education, ideally between final year at high school and first year of university, to understand a PDS.

We also see some evidence that the PDSs in general require investors to understand fewer finance terms. The percentage of finance terms in the prospectus and PDS are similar, as shown by the insignificant difference in the percentages. However, in terms of the percentage of the finance dictionary, there has been a 10% reduction, representing just under 140 words. This suggests that investors require considerably less awareness of finance terms and concepts than was previously the case. However, they do still require an understanding of over 100 terms. This is a considerable improvement in readability for investors.

4.3 Key Information Summary

The Financial Markets Conduct Act 2013 and the guidance from the Financial Markets Authority clearly outline information required within the PDS, and also some of the structure. One item of note is the so-called Key Information Summary (KIS) section, which is presented at the very start of the document, before even the contents page. This is a short section, serving as almost an executive summary for the offering, discussing the nature of the investment, the logistics of removing your money, and details about different types of funds the manager offers, including the risk level, asset allocation and basic information about the fees. This summary covers much of the information a person needs to make a decision, albeit in considerably less detail than is contained in the rest of the document.

When we compare the KIS with the rest of the document we observe that the KIS is relatively short, has higher readability, and uses fewer unique and unique finance words. The implication of this is that the KIS is generally easier to read as a result of having shorter sentences, and requiring a smaller vocabulary and less understanding of finance.

Table 3: Components of the Product Disclosure Statement

	PDS - Key Information Summary			PDS - Rest of Text			Difference in Averages
	Average	Minimum	Maximum	Average	Minimum	Maximum	
Number Words	709.52	395	1200	4408.33	2699	5670	-3698.81***
Number Sentences	49.29	25	89	273.33	183	373	-224.05***
Words Per Sentence	14.71	11.31	17.95	16.29	11.83	19.47	-1.58***
% Complex	15.08%	12.17%	19.83%	15.22%	13.83%	17.65%	-0.14%
Fog Index	11.92	10.26	13.70	12.61	10.43	14.31	-0.69**
% Unique Finance Words	0.28%	0.21%	0.39%	1.00%	0.69%	1.22%	-0.71%***
% Doc Finance Words	14.83%	10.95%	17.58%	12.06%	10.25%	14.18%	2.77%***
% Dict	2.56%	1.55%	3.47%	7.37%	5.17%	9.16%	-4.82%***

Note: For each of the 21 PDS documents we separate the documents into the Key Information Summary and the rest of the document. *Number of Words* is defined as the total number of words in the document after excluding abbreviations, names and addresses. *Number of Sentences* is defined as the number of non-heading sentences in the document. *Words per Sentence* is defined as number of words in the document divided by the number of sentences. *% Complex* is defined as the number of words contained three or more syllables divided by the total number of words in the document. The number of syllables was sourced from the Loughlin-McDonald 2011 master dictionary. *Fog Index* is calculated as per equation 1. *% Unique Finance Words* is the number of unique words from the Campbell Harvey hypertext finance dictionary contained within the document as a percentage of the total number of words in the finance dictionary. The finance dictionary was amended to include terms related to NZ. *% Doc Finance Words* is defined as the sum of the number of times each word contained in the finance dictionary occurs divided by the total number of words in the document. *% Dict* is defined as the total number of unique words contained in the document as a percentage of the number of words in the master dictionary. Significance of the difference in averages was calculated using a matched pairs *t*-test. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

5. Conclusion

Overall we find that the PDS documents are a marked improvement over the prospectuses that fund managers were required to provide previously. There is a significant reduction in the complexity of the language used and the amount of finance jargon contained with the PDS. However, we do observe an increase in the length of the sentences which can make documents more difficult to read. One observation, however, is that the PDS has encouraged fund managers to use more bullet pointed lists and tables rather than more traditional paragraphs. This may be responsible for the increased sentence length, and may in fact improve an investor's ability to understand the information contained. It is also worth noting that while PDS documents are significantly shorter and appear to be easier to understand, it is still not clear if a typical KiwiSaver investor would be able to understand the information they contain.

While the PDS does appear to have made improvements in some areas, several open questions remain. For example, are the word limits for the PDS appropriate (especially given the significant difference in the number of offerings between fund providers)? What is the best size of a PDS to maximise the number of investors engaging with the document? Does the Key Information Summary provide enough information for investors to make a decision solely based on it (without the PDS)? Lastly, it is unclear whether the move toward simplified disclosure will be enough to encourage investors to rely more heavily on the PDS when making KiwiSaver decisions. The answers to these questions will be the subject of ongoing work, given the importance of ensuring investors are well-placed to make informed decisions.

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FLIGHT OF THE CONDORS: EVIDENCE ON THE PERFORMANCE OF CONDOR OPTION SPREADS IN AUSTRALIA

SCOTT J. NIBLOCK[1*]

1. Lecturer, School of Business & Tourism, Southern Cross University, Australia

* Corresponding Author: Dr Scott J. Niblock, Lecturer, School of Business & Tourism, Southern Cross University, Gold Coast, Australia ☎ +61 7 5589 3098 ✉ scott.niblock@scu.edu.au

Abstract: This paper examined whether superior nominal and risk-adjusted returns could be generated using condor option spread strategies on a large capitalized Australian stock. Monthly Commonwealth Bank of Australia Ltd (CBA) condor option spreads were constructed from 2012 to 2015 and their returns established. Standard and alternative measures were used to determine the nominal and risk-adjusted performance of the spreads. The results show that the short put condor spread produced superior nominal and risk-adjusted returns, but seemingly underperformed when the upside potential ratio was taken into consideration. The long iron condor spread also offered reasonable returns across both performance metrics. On the other hand, the short call condor, long call condor, short iron condor and long put condor spreads did not perform as well on a nominal and risk-adjusted return basis. The results suggest that constructing spreads on the foundation of volatility preferences could be a driver of performance for condor option spreads strategies. For instance, short volatility condor spreads with negatively skewed return distribution shapes appear to add value, while long volatility condor spreads with positively skewed return distribution shapes seem to be less attractive over the sample period. Overall, condor option spreads demonstrate high risk-return profiles, offer versatility in their construction and intended pay-off outcomes, create value in some instances and can be executed across varying market conditions. It is suggested that risk averse investors best avoid condor option spreads, while those with above average risk tolerances may be well suited to the strategies, particularly short volatility-driven condor spreads.

Keywords: Condor; Options; Return; Risk; Spread; Volatility.

1. Introduction

Options are becoming increasingly popular with investors seeking alternative investments and greater versatility (McKeon, 2016). CME Group (2015) claim that the popularity of options in the US post-global financial crisis (GFC) period has grown from approximately 30 million contracts traded monthly in 2009 to 50 million in 2014. Option-based investment strategies have also seen solid growth over the last decade. For instance, US option-based equity funds have risen from 12 in 2003 to 119 in 2014, signifying almost a 900% increase and over $46 billion in assets under management (AUM) (Black and Szado, 2015).

Option spreads are an example of one of the many options-based strategies available to investors. Option spread strategies are considered by practitioners and sophisticated investors to be flexible investment vehicles, accounting for a growing proportion of the calls and puts traded in options markets (Chaput and Ederington, 2003; Falenbrach and Sandås, 2010; McKeon, 2016). For example, Chaput and Ederington (2003) reveal that option spread trading totals 29 per cent of Eurodollar option trading volume, while Falenbrach and Sandås (2010) show that vertical call and put option spread trading represents 16 per cent of FTSE 100 index option trading volume.

Essentially, option spreads are limited risk, directional or non-directional strategies that are constructed to generate a limited profit when volatility is expected to fall or rise (McKeon, 2016). Up to four legs are involved in most option spread strategies and a net debit/credit is outlaid/received for each position. The main benefit of option spread trading is that the strategies can be setup for anticipated market conditions over the intended holding period; thus, allowing investors to target investment goals that are tailored to their desired risk-return profiles (Niblock and Sinnewe, forthcoming). The pay-offs are also defined upfront, so while potential profits from the strategies are capped, so are the associated losses.

So do option spread strategies add value? And under what circumstances should the strategies be utilized? The international evidence is well established and generally appears to be supportive of option-based strategies (Chaput and Ederington, 2005, 2008; Hill et al, 2006; McKeon, 2016; Whaley, 2002). While numerous studies have empirically examined the performance of option-based strategies, only a few have been carried out in an Australian market setting, mainly focusing on covered call writing (El-Hassan et al, 2004; Frino and Wearin, 2004; Jarnecic, 2004; Mugwagwa et al, 2012; Niblock and Sinnewe, forthcoming; O'Connell and O'Grady, 2014).

Given the sparsity of evidence and their perceived benefits and costs, the performance of option spread strategies in Australia remains unclear, particularly those pertaining to 'condor' option spreads. Therefore, further empirical investigation is warranted. The aim of this paper is to examine the nominal and risk-adjusted return performance of Commonwealth Bank of Australia Ltd (CBA) monthly condor option spread strategies from 2012 to 2015. For comparative purposes, both standard and alternative performance measures are employed. The research question is:

'Do condor option spreads demonstrate superior nominal and risk-adjusted return outperformance in Australia?[1]

To address this question, two propositions are posed:

***P**$_1$: Superior nominal returns cannot be produced using CBA condor option spreads*

***P**$_2$: Superior risk-adjusted returns cannot be produced using CBA condor option spreads.*

The value of this study is that it is the first to empirically investigate the nominal and risk-adjusted return performance of condor option spreads in an Australian context. A comprehensive performance analysis of condor option spreads across various setups

[1] Condor option spreads are limited risk, non-directional strategies that are constructed using short-dated calls and/or puts to generate a limited profit when volatility is low or high.

will offer a better understanding of the role of option-based strategies in Australia, particularly on large capitalized and popular stocks like CBA. The results of this study will attempt to establish whether the strategies are a value-add for funds managers, traders and investors pursuing greater risk-return payoffs in the Australian stock market. They will also be of interest to those seeking alternative investments as a result of the limited availability of Australian retail financial products (Australian Treasury, 2014).

The main findings indicate that the short put condor spread produced superior nominal and risk-adjusted returns compared to the S&P/ASX 200 index, but seemingly underperformed when the upside potential ratio was taken into consideration. The long iron condor spread also offered reasonable returns across both performance metrics. Similar to McKeon (2016), these findings suggest that credit or 'short volatility' condor spreads appear to add value for investors seeking negatively skewed return distribution shapes. On the other hand, the short call condor, long call condor, short iron condor and long put condor spreads did not perform as well on a nominal and risk-adjusted return basis, particularly the debit or 'long volatility' condor spreads. The remainder of the paper is organized as follows. Section 2 highlights key literature. Section 3 describes the data and methods employed. Section 4 presents the empirical results. Section 5 discusses the implications of the results and proposes ideas for future research.

2. Literature Review

There remains a large amount of academic scrutiny and ongoing debate over whether option-based investment strategies generate superior performance (Mugwagwa et al, 2012). Some studies claim that covered call writing, for instance, demonstrates the potential to produce above average risk-adjusted returns (El-Hassan et al, 2004; Frino and Wearin, 2004; Hill et al, 2006; Jarnecic, 2004; Niblock and Sinnewe, forthcoming; O'Connell and O'Grady, 2014; Whaley, 2002). On the contrary, there is evidence to suggest that option-based strategies may actually weigh on investment returns and are inefficient methods of allocating wealth (Bookstaber and Clarke, 1984; Booth et al, 1985; Hoffmann and Fischer, 2012; Lhabitant, 1999; Merton et al, 1978; Mugwagwa et al, 2012). Hoffmann and Fischer (2012) maintain that option-based strategies can only be profitable in a mean-variance framework if the writer/taker can predict stock prices during the holding period (Reilly and Brown, 1997) and if call or puts are mispriced due to uncertainty associated with estimating volatility (Benninga and Blume, 1985; Black, 1975; Figlewski and Green, 1999; Hill et al, 2006; Leggio and Lien, 2002; Rendleman, 2001); thus, inferring market inefficiencies (Black and Scholes, 1972; Fama, 1998).

Given that option-based strategies have been found to exhibit asymmetric return distributions, a mean-variance analysis of their performances may not be appropriate (Bookstaber and Clarke, 1984; Booth et al, 1985; Lhabitant, 1999; Merton et al, 1978). For example, option spread trading shortens the positive/negative tail of the return distribution resulting in negative/positive skewness and decreases components of the variance; that is, upside/downside risk (Bookstaber and Clarke, 1984). Claims of outperformance based on the assumption that option returns produced from such strategies are normally distributed can therefore be misleading. This is particularly the case when variance is deemed to be a reliable measure of risk in asymmetric return distributions (Board et al, 2000; Leggio and Lien, 2002). Further, variance treats upside and downside risk symmetrically. As investors dislike investments with low returns and prefer investments with high returns, employing mean-variance performance measures (such as the Sharpe, Information and Jensen ratios) may lead to biased conclusions when assessing the non-linear payoffs of option spread strategies (Bernardo and Ledoit, 2000; Board et al, 2000; Groothaert and Thomas, 2003; Hübner, 2016; Mahdavi, 2004; O'Connell and O'Grady, 2014).[2]

Despite these issues, the academic literature pertaining to option spread trading is limited. This is surprising given the volume of literature on covered call writing and subsequent controversy surrounding the performance of option-based investment strategies. To the best of the author's knowledge, there are only a handful of empirical studies which address the performance of option spreads (see Chaput and Ederington, 2005, 2008; McKeon, 2016). Chaput and Ederington (2005, 2008) investigate Eurodollar option spread trades and find that they appear to reduce costs and/or increase profits associated with long out-of-the-money strike positions. McKeon (2016) examines bull call option spread trade setups using the S&P 500 index and finds that spreads held until maturity produce high average returns and negative/positive skewness in short/long volatility positions. McKeon further claims that short positions in out-of-the-money calls offer the strongest average returns, both before and after transaction costs.

3. Data and Methods

Closing prices, strikes and expiry dates for monthly Commonwealth Bank of Australia Ltd (CBA) call and put option series are sourced from the Thomson Reuters Tick History (TRTH) database. Monthly closing prices for CBA[3] and S&P/ASX 200 index data[4] are obtained from the S&P Capital IQ database. The investigation is restricted to CBA due to its size[5] and high positive correlation with the Australian stock market[6] (see Figure 1 below). CBA is also a highly liquid and sufficiently volatile stock (see Figure 2 below), thus presenting as a good proxy for the Australian stock market and an ideal candidate for condor option spread trading.

CBA condor option spreads are back-tested over a 36-month period from August 2012 to July 2015, with the sample period being determined by the availability of call and put option price data. Specifically, short-dated condor option spreads are executed at month-end expiration dates over CBA, with an expiry date in the following month. No early exercise is assumed and positions are kept open until expiration.[7] For margin purposes, it is assumed that shares in CBA or equivalent cash collateral are not held. As such, short call and put options are written naked, with ASX Clearinghouse margin requirements and transaction costs being ignored. To avoid any zero premiums on the CBA call and put series under investigation, the monthly option price is in some cases

[2] Standard performance measures do not account for skewness and kurtosis and may overstate performance (Lhabitant, 2000; O'Connell and O'Grady, 2014).

[3] Monthly CBA closing prices are not adjusted for dividends and franking credits.

[4] The S&P/ASX 200 index is one of the largest capitalization-based indexes, covering approximately 80% of Australian stock market capitalization (Standard and Poors, 2017). Monthly ASX 200 index closing prices are not adjusted for dividends and franking credits.

[5] CBA is the largest company on the Australian stock market by capitalization (Standard and Poors, 2017).

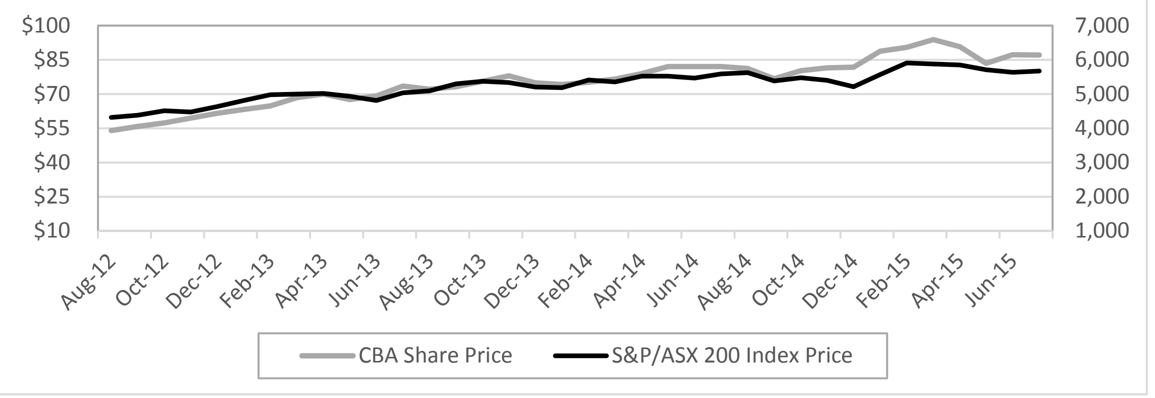
[6] CBA is highly positively correlated with the ASX 200 index; thus, CBA is considered a proxy for the Australian stock market in this study.

[7] Sometimes call and put options may be exercised before expiration. However, early exercise is mostly avoided due to time value associated with bought call and put options (Financial Times, 2015).

substituted by the settlement price. Where settlement prices are not available for the respective series, average monthly option prices over the sample period are employed.

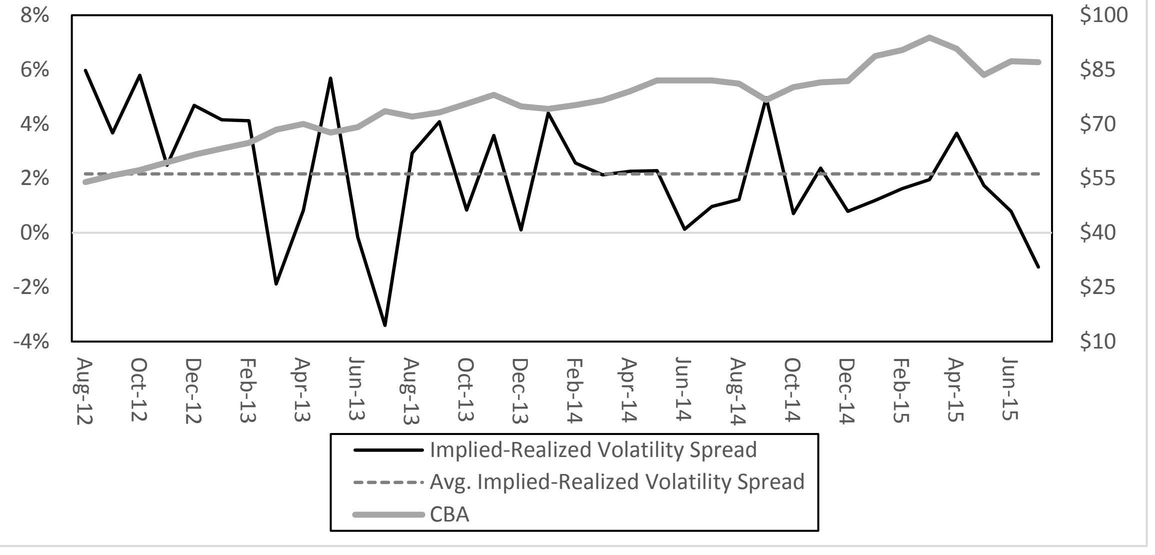
To estimate returns of the condor option spreads, CBA stock prices are established at month's t and t_{+1}.

Figure 1: CBA vs. S&P/ASX 200 price movement



Source: Capital IQ

Figure 2: CBA vs. S&P/ASX 200 volatility spread



Source: Capital IQ

CBA call and put option pricing data (i.e., option strikes and prices) are also identified at t with an expiry date in the following month t_{+1}.[8] CBA has multiple tradeable series in month t_{+1}, however, for the purpose of condor option spread trading in this study, it is assumed that t_{+1} call and put options with strike prices equivalent to the stock price at month t are traded one strike in-the-money (*1ITM*) and up to three strikes out-of-the-

[8] ASX expiry for individual equity options is the fourth Thursday of each calendar month (ASX, 2017).

money (*1OTM, 2OTM* and *3OTM*).[9] Note: each strike employed represents the relevant price increment for individual 'American' equity options series set by the ASX (ASX, 2017). In this study, CBA strike prices are in increments of one dollar.

Monthly component option returns of the CBA condor options spreads are established at t and are based on whether the respective call and put series are OTM or ITM at monthly expiry $t+1$. If a long call (LC) or long put (LP) is OTM at expiry, it is assumed that it expires worthless and the taker's loss is limited to the option premium paid, with no further obligation; thus, the OTM LC and LP returns for month t are calculated as:

$$R_{t(OTM\_LC,\ OTM\_LP)} = -1 \tag{1}$$

If a LC or LP is ITM at expiry, exercise is assumed, the taker buys/sells shares from/to the call/put option writer at the nominated strike price and receives any price appreciation beyond the strike price; thus, the ITM LC and LP returns for month t under this scenario are calculated as:

$$R_{t(ITM\_LC)} = \frac{SP_{t+1} - STRK_t - OP_t}{OP_t} \tag{2}$$

$$R_{t(ITM\_LP)} = \frac{STRK_t - SP_{t+1} - OP_t}{OP_t} \tag{3}$$

where SP_{t+1}, $STRK_t$ and OP_t are the share price, strike price and option price at either $t+1$ or t, respectively. If a short call (SC) or short put (SP) is OTM at expiry, it is assumed that it expires worthless and the writer keeps the option premium received upfront from the taker, with no further obligation; thus, the OTM SC and SP returns for month t are calculated as:

$$R_{t(OTM\_SC,\ OTM\_SP)} = \frac{OP_t}{STRK_t} \tag{4}$$

where OP_t and $STRK_t$ are the option price and strike price at t, respectively. If a SC or SP is ITM at expiry, exercise is assumed, the call/put writer sells/buys shares to/from the option taker at the nominated strike price and is accountable for any price appreciation beyond the strike price; thus, the ITM SC and SP returns for month t under this scenario are calculated as:

$$R_{t(ITM\_SC)} = \frac{STRK_t - SP_{t+1} + OP_t}{STRK_t} \tag{5}$$

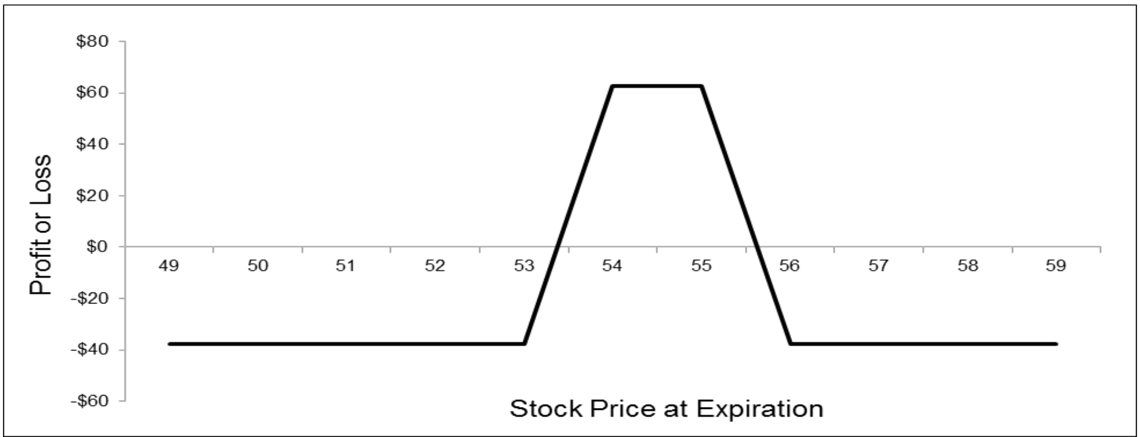
$$R_{t(ITM\_SP)} = \frac{SP_{t+1} - STRK_t + OP_t}{STRK_t} \tag{6}$$

[9] Hill et al, (2006) claims that trading shorter maturity and closer to the money options offers adequate open interest and volume and greater volatility premium.

where $STRK_t$, SP_{t+1} and OP_t are the strike price, share price and option price at either *t* or *t+1*, respectively.

Once the component option returns are determined, the CBA condor option spreads can be constructed and their associated returns established. In this study, six condor option spreads are examined, namely the: 1) long call condor; 2) long put condor; 3) long iron condor; 4) short call condor; 5) short put condor; and 6) and short iron condor. Note: condor option spread positions are constructed depending on market conditions (e.g., low or high volatility) and intended trading directions to produce desired payoffs. Such payoffs can be diametrically different or identical, which highlights the versatility of the strategies (see Figures 3 and 4 below). The long call condor (LCC) and long put condor (LPC) spreads are limited risk, non-directional strategies that are constructed to generate a limited profit when volatility is low. Four legs are included in the respective strategies and a net debit is outlaid for each position. Using call or put options expiring in the same month, a LCC/LPC spread can be implemented by buying a *1ITM* call/put, selling a *1OTM* call/put, selling a *2OTM* call/put and buying a *3OTM* call/put (see Figure 3). Note: a LCC position can also be constructed by combining a bull call spread and a bear call spread; while a LPC position can be achieved by combining a bear put spread and bull put spread.

Figure 3: Long call/put and iron condor spread payoff

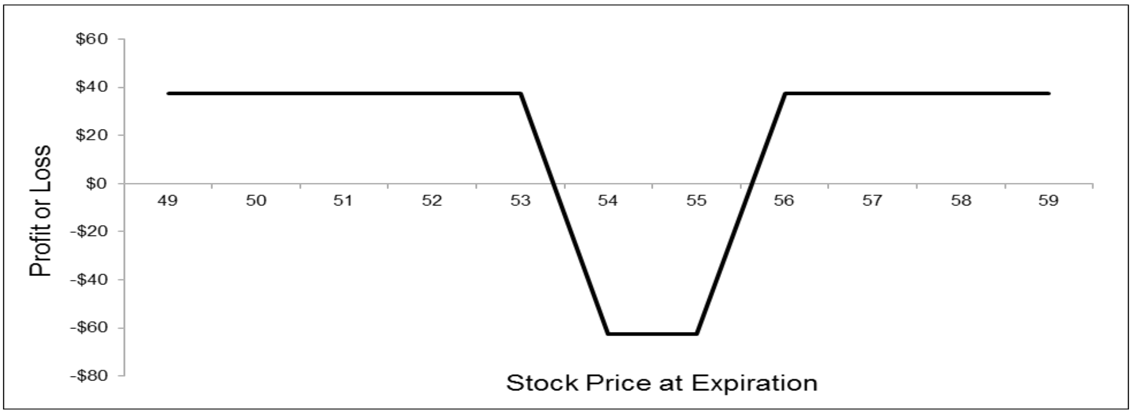


Source: Author

The long iron condor (LIC) spread is a limited risk, non-directional strategy that is constructed to generate a limited profit when volatility is high. Four legs are included and a net credit is received. Using call and put options expiring in the same month, a LIC spread can be implemented by selling a *1ITM* put, buying a *1OTM* put, selling a *2OTM* call and buying a *3OTM* call (see Figure 3 above). Note: a LIC position can also be achieved by combining a bull put spread and a bear call spread.

The short call condor (SCC) and short put condor (SPC) spreads are limited risk, non-directional strategies that are constructed to generate a limited profit when volatility is high. Four legs are included in the respective strategies and a net credit is received for each position. Using call or put options expiring in the same month, a SCC/SPC spread can be implemented by selling a *1ITM* call/put, buying a *1OTM* call/put, buying a *2OTM* call/put and selling a *3OTM* call/put (see Figure 4). Note: a SCC position can also be achieved by combining a bear call spread and a bull call spread; while a SPC position can be constructed by combining a bull put spread and bear put spread.

Figure 4: Short call/put and iron condor spread payoff



Source: Author

Finally, the short iron condor (SIC) strategy is a limited risk, non-directional strategy that is constructed to generate a limited profit when volatility is low. Four legs are included and a net debit is outlaid. Using call and put options expiring in the same month, a SIC spread can be implemented by buying a *1ITM* put, selling a 1*OTM* put, buying a *2OTM* call and selling a *3OTM* call (see Figure 4 above). Note: a SIC position can also be achieved by combining a bear put spread and a bull call spread.

The condor option spread returns at month *t* are calculated as:

$$R_{i,t(LCC)} = \frac{PROF_t(1ITM\_LC)+PROF_t(1OTM\_SC)+PROF_t(2OTM\_SC)+PROF_t(3OTM\_LC)}{STRK_t(1OTM\_SC)-STRK_t(1ITM\_LC)} \quad (7)$$

$$R_{i,t(LPC)} = \frac{PROF_t(1ITM\_LP)+PROF_t(1OTM\_SP)+PROF_t(2OTM\_SP)+PROF_t(3OTM\_LP)}{STRK_t(1ITM\_LP)-STRK_t(1OTM\_SP)} \quad (8)$$

$$R_{i,t(LIC)} = \frac{PROF_t(1ITM\_SP)+PROF_t(1OTM\_LP)+PROF_t(2OTM\_SC)+PROF_t(3OTM\_LC)}{STRK_t(1ITM\_SP)-STRK_t(1OTM\_LP)} \quad (9)$$

$$R_{i,t(SCC)} = \frac{PROF_t(1ITM\_SC)+PROF_t(1OTM\_LC)+PROF_t(2OTM\_LC)+PROF_t(3OTM\_SC)}{STRK_t(1OTM\_LC)-STRK_t(1ITM\_SC)} \quad (10)$$

$$R_{i,t(SPC)} = \frac{PROF_t(1ITM\_SP)+PROF_t(1OTM\_LP)+PROF_t(2OTM\_LP)+PROF_t(3OTM\_SP)}{STRK_t(1ITM\_SP)-STRK_t(1OTM\_LP)} \quad (11)$$

$$R_{i,t(SIC)} = \frac{PROF_t(1ITM\_LP)+PROF_t(1OTM\_SP)+PROF_t(2OTM\_LC)+PROF_t(3OTM\_SC)}{STRK_t(1ITM\_LP)-STRK_t(1OTM\_SP)} \quad (12)$$

where $R_{i,t}$ is the respective CBA condor option spread return; $PROF_t$ is the profit generated from the component call and/or put options (in dollars); and $STRK_t$ is the strike price of the component call or put options (in dollars).

To ensure that asymmetric return distributions associated with option-based strategies are accounted for, alternative 'non-linear' performance measures such as the Sortino ('downside risk') (Sortino and van der Meer, 1991) and upside potential ('upside risk')

(Sortino *et al*, 2003) ratios are utilized.[10] For comparative purposes, standard 'linear' performance measures such as the Sharpe (1966), Modigliani and Modigliani (1997) 'M²' (using both standard deviation (SD) and semi-standard deviation (SSD)) and Goodwin (1998) information ratios are employed. Consistent with the approach of Niblock and Sinnewe (forthcoming), a modified Jensen (1968) alpha model in ordinary least squares regression (OLS) form is also used. With this model, alpha (α_i) is designed to capture the excess risk-adjusted return of the condor option spread in relation to the ASX 200 index:

$$R_{i,t} - rf_t = \alpha_i + \beta_i (R_{m,t} - rf_t) + \varepsilon_{i,t} \qquad (13)$$

where $R_{i,t}$ is previously defined; rf_t is the 30-day Australian bank accepted bill (BAB) return; and $R_{m,t}$ is the monthly ASX 200 index return. Note: *p*-values from the Newey-West *t*-statistics are adjusted for autocorrelation up to 3 lags using the Schwarz automatic observation-based lag selection approach. To address **P**$_1$ and **P**$_2$, summary statistics and standard and alternative performance measures are evaluated in an attempt to establish whether CBA condor option spreads deliver superior nominal and risk-adjusted returns versus the ASX 200 index.

4. Empirical Results

Summary statistics for the CBA condor option spreads are shown in Table 1, Panel's A and B. Note: LCC and SCC, LPC and SPC and SIC and LIC spread combinations are the inverse of each other, and as such, produce perfectly negative correlation coefficients (-1.000). Hence, only positive nominal returns associated with SCC, SPC and LIC are highlighted and subsequently discussed. In Panel A, the average monthly returns of the SCC, SPC and LIC spreads (1.28%, 12.18% and 6.46%, respectively) are higher than the ASX 200 (0.58%).[11] This infers that the 'credit' condor spreads performed better than the broader market and their 'debit' condor spread peers (e.g., LCC, LPC and SIC) on a nominal basis over the sample period. Further, the credit condor option spreads produced up to 21 times more return than the ASX 200 index, suggesting that the strategies provide large returns, but are also inherently risky. Notably, a t-test reveals that the average return for the SPC spread is positive and statistically significant at the 10% level. This indicates that the SPC spread significantly outperformed the ASX 200 index on a nominal return basis. All remaining t-tests were statistically insignificant. Based on these findings, **P**$_1$ is rejected for the SPC condor option spread, with the remaining spreads accepting **P**$_1$.

The condor option spreads demonstrate higher total and downside risk than the ASX 200 index. For instance, the standard deviations of the spreads range between 40.26% and 45.75% compared to 3.02% for the ASX 200, while the semi-standard deviations of the spreads range between 24.54% and 35.25% compared to 2.12%. The SCC spread has the highest standard deviation (45.75%) and the SPC spread the lowest (40.26%), which suggests that call-based condor spreads carry greater total risk than put-based and call

[10] It should be recognized that option-based strategies generally produce non-normal return distributions due to their asymmetric nature. Such asymmetry may undermine the use of traditional risk measures. For instance, the mean-variance framework treats upside and downside risk symmetrically, which can lead to erroneous conclusions when examining the performance of option-based strategies (McKeon, 2016; Mugwagwa et al, 2012; Niblock and Sinnewe, forthcoming; O'Connell and O'Grady, 2014). Thus, any evaluation of condor option spread performance should be treated with caution when using standard performance measures.

[11] Frequent exercise and unaccounted transaction costs associated with condor option spread trading may have influenced the return performances reported in this study.

and put-based condor spread combinations. On the other hand, the SCC spread has the highest semi-standard deviation (35.25%) and the LIC spread the lowest (24.54%). With the exception of LIC, credit condor spreads appear to produce greater downside risk than their debit spread counterparts (e.g., LCC, LPC and SIC). Further, condor option spreads generate up to 15 times more total risk and up to 17 times more downside risk than the ASX 200 index.

Table 1: Summary statistics

Significance level: * 10%; ** 5%; *** 1%. SCC is short call condor. SPC is short put condor. LIC is long iron condor. ASX200 is S&P ASX 200 index. Full results are available from author upon request.

Panel A - Descriptives

	SCC	SPC	LIC	ASX200
Mean	1.28%	12.18%	6.46%	0.58%
T-stat.	0.0912	1.7237*	0.8496	NA
Median	21.50%	21.00%	-6.25%	0.36%
Max.	81.00%	116.00%	100.50%	6.88%
Min.	-88.50%	-94.00%	-44.00%	-7.69%
Std. Dev.	45.75%	40.26%	41.40%	3.02%
Semi-Std. Dev.	35.25%	32.45%	24.54%	2.12%
Excess St. Dev.	46.46%	40.21%	41.02%	NA
Skewness	-0.5104	-0.8154	0.7134	-0.1884
Kurtosis	2.1690	4.4106	2.1636	3.2922
Jarque-Bera	2.5990	6.9735**	4.1028	0.3411
Obs.	36	36	36	36

Panel B – Correlation coefficients

	SCC	SPC	LIC	ASX200
SCC	1.0000			
SPC	-0.1879	1.0000		
LIC	-0.8416***	0.3622**	1.0000	
ASX200	-0.2060	0.0537	0.1596	1.0000

Condor option spread return distributions are also more skewed than the ASX 200 (-0.1884). For example, the LIC spread is positively skewed (0.7134), while the SCC and SPC spreads are negatively skewed (-0.5104 and -0.8154, respectively). The ASX 200 index return distribution produces a relatively normal tail (3.2922). Conversely, the SPC spread is more heavy-tailed (4.4106), while the LIC and SCC spreads are more light-tailed (2.1636 and 2.1690, respectively). Non-normal return distributions are particularly evident in the SPC spread (6.9735), with the reported Jarque-Bera test statistics being significant at the 5% level. In Panel B, the correlation measures for the pairwise condor option spread combinations are presented. The LIC spread is correlated with the SCC (-0.8416) and SPC (0.3622) spreads, and are statistically significant at the 5% level or better. All remaining spread combinations are statistically insignificant. The statistically significant correlations discovered suggest that synthetic condor option spread positions may be constructed depending on market conditions and intended trading directions, which again highlights the versatility of the strategies.

Risk-adjusted performance measures for the CBA condor option spreads are presented in Table 2. Note: LCC is the counterparty of SCC, LPC is the counterparty of SPC and SIC is the counterparty of LIC. Again, similar to the summary statistics, only positive risk-adjusted returns associated with SCC, SPC and LIC are highlighted and subsequently discussed. With the exception of the SPC and LIC spreads, the Sharpe and M^2 (SD) ratios show that condor spreads are more exposed to total risk and produce lower risk-adjusted returns than the ASX 200 index. For instance, using the Sharpe ratio, the SCC (0.0230) spread underperformed the ASX 200 (0.1177), while the SPC (0.2969) and LIC (0.1506) spreads outperformed. To explain in percentage terms, the M^2 (SD) ratio indicates that on a risk-adjusted return basis the SPC spread outperformed the ASX 200 index by 0.54% monthly. The information ratios reveal that condor spreads have mixed excess volatility and risk-adjusted return performance when compared to the ASX 200 index. For instance, the information ratios for the SCC (0.0150), SPC (0.2884) and LIC (0.1433) spreads outperformed the ASX 200.

Table 2: Risk-adjusted performance measures

Significance level: * 10%; ** 5%; *** 1%. *p*-values from the Newey-West *t*-statistics are adjusted for autocorrelation up to 3 lags using the Schwarz automatic observation-based lag selection approach. SD is standard deviation. SSD is semi-standard deviation. Full results are available from author upon request.

	SCC	SPC	LIC	ASX200
Sharpe Ratio	0.0230	0.2969	0.1506	0.1177
M^2 Ratio (SD)	-0.29%	0.54%	0.10%	NA
Information Ratio	0.0150	0.2884	0.1433	NA
Jensen Alpha	0.0216	0.1171	0.0546	NA
T-stat.	0.2861	1.8076*	0.7875	NA
Sortino Ratio	0.0298	0.3684	0.2540	0.1679
M^2 Ratio (SSD)	-0.29%	0.42%	0.18%	NA
Upside Potential Ratio	0.5534	0.4148	0.7143	0.5565

Further, the modified Jensen alphas demonstrate that condor option spreads (with the exception of the SPC spread) do *not* generate higher risk-adjusted returns than the ASX 200 index. After adjusting for systematic risk, the SCC (0.0216), SPC (0.1171) and LIC (0.0546) spreads produced positive alphas. The SPC spread delivered the greatest outperformance versus the ASX 200, being statistically significant at the 10% level.

Standard 'linear' performance measures can be problematic when considering the risk-adjusted return performance of condor option spreads however. This is due to the asymmetric nature of the strategies and the use of standard deviation as the nominated risk measure, but can be alleviated by the use of downside and upside risk performance measures such as the Sortino and M^2 (SSD) and upside potential ratios, respectively (El-Hassan *et al*, 2004; Niblock and Sinnewe, forthcoming). With the exception of the SPC and LIC spreads, the Sortino and M^2 (SSD) ratios show that condor spreads have a greater exposure to downside risk and generate lower risk-adjusted returns than the ASX 200 index. For example, using the Sortino ratio, the SCC spread (0.0298) underperformed the ASX 200 (0.1679), while the SPC (0.3684) and LIC (0.2540) spreads outperformed.

Of the condor spreads, the SPC spread had the highest Sortino ratio. In percentage terms, the M^2 (SSD) ratio indicates that on a risk-adjusted return basis the SPC spread outperformed the ASX 200 index by 0.42% monthly. On the other hand, the upside potential ratios revealed that condor option spreads have mixed upside risk-adjusted return performance. For example, the upside potential ratios for the LIC spread (0.7143) outperformed the ASX 200 (0.5565), while the SCC (0.5534) and SPC (0.4148) spreads underperformed. Again, based on the weight of evidence presented, $\mathbf{P}_2$ is rejected for the SPC condor option spread, with the remaining spreads accepting $\mathbf{P}_2$.

5. Conclusion

This paper investigated whether superior nominal and risk-adjusted returns could be generated using monthly condor option spread strategies on a large capitalized Australian stock (i.e., Commonwealth Bank of Australia Ltd (CBA)) from 2012 to 2015. The results of this study are mostly consistent with the limited empirical option spread performance studies conducted to-date (see Chaput and Ederington, 2005, 2008; McKeon, 2016). Specifically, the findings indicate that the SPC spread produced superior nominal and risk-adjusted returns compared to the ASX 200 index, but seemingly underperformed when the upside potential ratio was taken into consideration. The LIC spread also offered reasonable returns across both performance metrics. Similar to McKeon (2016), these findings suggest that credit or 'short volatility' condor spreads appear to add value for investors seeking negatively skewed return distribution shapes.

On the other hand, the SCC, LCC, SIC and LPC spreads did not perform as well on a nominal and risk-adjusted return basis, particularly the debit or 'long volatility' condor spreads (e.g., LCC, SIC and LPC). Therefore, constructing spreads on the basis of short or long volatility preferences could be a driver of performance for condor option spreads strategies. For instance, writing/buying calls and/or puts during periods of heightened market volatility may be particularly advantageous/disadvantageous for credit/debit condor spreads (McKeon, 2016; Niblock and Sinnewe, forthcoming). Outperformance/underperformance of the market (e.g., ASX 200 index) could also be explained by the potential overpricing of written/bought call and/or puts options during such periods (Figelman, 2008; Hill et al, 2006; Kapadia and Szado, 2007; McIntyre and Jackson, 2007; O'Connell and O'Grady, 2014; Simon, 2011, 2013).

Overall, the evidence presented suggests that with the exception of the SPC spread, condor option spread strategies do not produce superior nominal or risk-adjusted returns. They do however, demonstrate high risk-return profiles, offer versatility in their construction and intended pay-off outcomes, create value for investors in some instances (i.e., SPC) and can be executed across varying market conditions. For example, the SPC spread strategy is particularly useful for investors seeking speculative positions in upward trending price and/or volatile market environments. Moreover, converting uncertain future capital gains into immediate cash flows appears to be advantageous for investors pursuing short volatility positions. It is therefore suggested that risk averse investors best avoid condor option spreads, while those with above average risk tolerances may be well suited to the strategies, particularly short volatility-driven condor spreads.

The value of this study is that it is the first to empirically examine the nominal and risk-adjusted return performance of condor option spreads in Australia. The results are useful for funds managers, traders, investors and academics evaluating the performance of condor option spread strategies. The research also builds on the work of McKeon (2016), who shows that short volatility call option spread trades on S&P 500 index options held until maturity produce high average returns and strong negative skewness, both before and after transaction costs. Further, the study adds to our understanding of the performance of condor option spreads by supporting findings in the Australian options literature (see Niblock and Sinnewe, forthcoming). For example, credit condor spreads have the potential to generate superior nominal and risk-adjusted returns over the ASX 200 index, which could be attributable to the overpricing of call and put options in Australia.

It should be borne in mind however, that the results only captured market conditions/settings specific to the stock chosen (e.g., CBA), option spread employed (e.g., condor) and holding period under investigation (e.g., monthly data from 2012 - 2015). The performances reported could be attributable to market/asset location and direction and volatility and liquidity factors. Costs associated with frequent trading and exercise were also not accounted for. Thus, the findings should be treated with caution, as they do not represent all potential risk-return characteristics and pay-offs pertaining to option spread trading in the Australian market (El-Hassan et al, 2004; Niblock and Sinnewe, forthcoming).

To overcome these limitations, future research could replicate the approach adopted in this study but across different Australian markets/sectors/companies, time periods, data intervals, option spreads (e.g., butterfly, calendar, condor, diagonal and/or vertical spreads) and option moneyness. Researchers exploring option spread performance are also encouraged to consider option market liquidity, volatility and transaction costs under this setting (Hill et al, 2006; McKeon, 2016). It is anticipated that such research will expand the literature on this interesting and under-researched topic by providing a better understanding of option spread trading in Australia. The further development of option strategies that attempt to mitigate risk and enhance returns are clearly desirable outcomes for modern investors.

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