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DISPERSION TRADING STRATEGY ON THE S&P100

Aldert Joaquim Zwart

Work project carried out under the supervision of:

Paulo Manuel Marques
Rodrigues

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Abstract

This study provides an empirical analysis back-testing a dispersion trading strategy to verify its performance. Dispersion trading is an arbitrage trading technique exploiting the difference between option prices of the index and its constituents. Price discrepancies are traced from literature to the correlation risk premium and net buying pressure of puts of the index. The strategy tends to outperform the general market. Cumulative returns of the strategy have beaten the Vanguard Total Market Index ETF, providing risk-adjusted returns in alpha and small beta indicating a strategy that is prone to systematic market risks.

Keywords: options, implied correlation, implied volatility, dispersion trading, market making, market inefficiency

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I. Theoretical framework / Literature review

This paper aims to test a dispersion trading strategy on the CBOE derivatives market, gauging the efficiency of the market with the possibility of generating excess returns while implementing different entry strategies. Most empirical analyses focus on one entry strategy. This paper will provide empirical evidence regarding the performance of different entry signals.

A dispersion trading strategy uses the fact that the difference between implied and realized volatility is greater between index options than its individual components. One could sell options on the index and buy individual stock options, which results in the price discrepancy of the implied volatility (Quantpedia n.d.). Empirical evidence of dispersion trading strategy is supported by for instance Buraschi, Trojani and Vedolin (2009), (Ferrari, Poy and Abate 2019), Marshall (2009), Nelken (2006), Schneider and Stubinger (2020) & Deng (2008). See Table 1 in Appendix I with returns & Sharpe ratios from previous studies. Deng (2008) provided empirical evidence that returns decreased after 2000 due to structural changes in the market. However, Marshall (2009) indicates that adding an entry signal will improve returns significantly.

Using performance metrics such as Sharpe ratios, which are mentioned in Table 1 in Appendix I, could reflect a biased view of the performance as returns are generated by misplacing the correlation risk which is not taken into consideration by Sharpe ratios Buraschi, Kosowski and Trojani (2014).

Several papers have focused on the sources of mispricing that enable returns for dispersion trading strategies. Extensive empirical evidence provided by Moskowitz (2003) and others suggests that correlation between assets' returns vary over time. In addition, the empirical research of Moskowitz (2003) provided insights into the phenomenon called "panic sell-off", where correlation increases during times of uncertainty and returns are lower. As a result, dispersion trading cannot be seen as a hedge against market sell-off, as the strategy is being short on correlation. According to Cochrane, Longstaff and Santa-Clara (2008) stock returns are correlated due to the correlation of the individual stock with the aggregate endowment also known as the diversification effect. However, Driessen, Maenhout and Vilkov (2009) also states that limits-of-arbitrage derives when introducing market frictions such as transaction costs and margin requirements during the exploitation of a strategy aiming at the priced correlation risk. Finally, Faria, Kosowski and Wang (2022) provided empirical evidence of a global correlation risk premium where co-movements of realized correlation, implied correlation and the correlations risk premiums across different European markets and US markets are very high.

Besides the correlation risk premium, different studies suggest that index options are over-valued due to net buying pressures. According to Bollen and Whaley (2004), net buying and selling pressures as index options are used as a hedge for general market downside risk. Deviations in implied volatility are directly related to the net buying pressure from the order flow. More specifically, changes in implied volatility of the S&P500 options are most strongly affected by puts while individual options are affected by call option demand. In addition, Goyal and Saretto (2008) provided evidence of the difference in implied volatility between the index and its components, by using a straddle strategy; selling the index and buying the components. Ryu, Ryu and Yang (2021) extended the research of Bollen and Whaley (2004) which decomposes different investor strategies, first buying pressure by direction trading (delta-informed) and secondly volatility traders (vega-informed). Both trading roles were significant in explaining the changes in implied volatility.

Different dispersion strategies are described by Bossu and Carr (2014). The first strategy mentioned is the plain vanilla dispersion strategy, this strategy tends to be liquid, cost-effective and customizable. However, one needs to hedge against price movements of the underlying asset in order to focus on arbitrage opportunities. Delta hedged dispersion trading strategies returns are purely based on differences in implied and realised volatility. An alternative strategy involves delta-hedging an option position: If the investor is successful in hedging away the priced risk, then a major element of the profit or loss from this strategy is the difference between the realized volatility and the expected volatility of the option according to Buraschi, Trojani and Vedolin (2009),. Nelken (2006) introduced a dispersion trading strategy including variance swaps. This reduces rebalancing costs and the variance helps to maintain a Vega exposure. Vega represents the rate of change of the value of the options with respect to the volatility of the underlying asset Hull (2012).

As stated before, Deng (2008) provided evidence of a decrease in the performance of dispersion trading strategies after 2000. In contrast, Marshall (2009) provides empirical evidence that timing the dispersion strategy will significantly improve performance. Marshall (2009) employs a more efficient version of the variance equation presented by Markowitz (1952). They modified the equation in order to produce the standard deviation of the portfolio's return rather than the variance of the portfolio's return and named it Markowitz-implied volatility (MIV). Also, the implied volatility of the index is extracted directly from the index itself called; index-option-implied-volatility (IOIV). The null hypothesis is that MIV=IOIV if the law of one price exists. Deviations from the null hypothesis result in arbitrage trading opportunities and therefore a trade entry signal. Nelken (2006) used the historical correlation matrix in conjunction with the implied volatility. The goal is to estimate the implied correlation matrix with the historical correlation matrix. A long dispersion position is set when the implied correlation matrix is larger than the historical one. Ferrari, Poy and Abate (2019), used a timing indicator on a daily basis with the difference between the implicit correlation of the index and the sample correlation of the components measured over a 30-day-rolling window. As a result, a long position is set when the signal is high and a short position when the signal is low. As stated before, correlation increases during periods of higher volatility. Forecasting implied and realized volatility could contain additional information for structuring an entry signal. According to Kambouroudis, McMillan and Tsakou (2016) realized volatility in the EU market could be best forecasted with an ARMAX model and implied volatility with an asymmetric GARCH.

This research aims to exploit arbitrage trading possibilities occurring due to market inefficiencies that are arising from the difference between the implied volatility of the index and its constituents. Previous studies from Deng (2008) and Ferrari, Poy and Abate (2019) will be adopted as a benchmark and will lead in example. As a deviation from these studies the performance of different entry signals will be tested which will contribute with a novel analysis to the currently existing literature. The remainder of this research is structured as follows. Section II will describe the model set-up. Section III will discuss how and which data is retrieved, followed by section IV, where the results will be set out. Finally, section V will conclude based on the results.

II. Model setup

Financial markets are subjected to transaction costs. Reducing the index constituents improves the impact of the cost. A dimensionality reduction model is used to identify a subset of the index. The weights of the subset are calculated via a Principal Components Analysis (PCA). The PCA was introduced by Jolliffe (2002), which reduces the dimensionality of a data set consisting of a large number of interrelated variables. This study uses the framework presented by Christoffersen, Fournier and Jacobs (2018). The framework transforms the sample of correlated variables into a sample of uncorrelated ones. This approach is also adopted by Deng (2008) and Ferrari, Poy and Abate (2019).

PCA / Tracking Portfolio

The framework requires first the calculation of returns from the prices of the individual as,

$$r_{i,t} = ln\left(\frac{S_{i,t}}{S_{i,t-1}}\right) \qquad (1)$$

Where $S_{i,t}$ corresponds to the price for equity i at time t. The returns are used to calculate the covariance matrix,

$$V(R) = \frac{R*R*}{n} = \begin{pmatrix} \sigma_{1,1}^2 & .. & \sigma_{1,k} \\ .. & .. & .. \\ \sigma_{k,1} & .. & \sigma_{k,k}^2 \end{pmatrix} \qquad (2)$$

The covariance matrix presents the variability in the dataset which represents the amount of information stored in the data. The PCA will decompose the covariance matrix in a set of uncorrelated variables without losing the stored information. R* is an n× k matrix of demeaned returns, where n is the length measured in days of the time series of returns for each stock, and k is the number of stocks. The application of the eigenvalue decomposition will order the eigenvectors of the covariance matrix explained by the share of variance. The top 20 of the shares derived from the variance V(R) is regressed on the returns of the index without intercept. The statistically insignificant securities are discarded and the regression process is repeated. Finally, the coefficients of the regression are used as the weights further in the research.

Implied Correlation & Dispersion

As stated before, implementing an entry signal will improve the total performance of the strategy. The entry a trade will be based on the discrepancy of the index´s and constituents implied volatility and implied correlation. The amount dispersion (the difference between implied volatility of the index and its constituents is calculated, according to (CBOE 2021), as,

$$Dispersion = \sum_{i=1}^{N} wi\sigma_i^2 - \sigma_{Index}^2. \qquad (3)$$

Dispersion trading strategies, when focusing on the correlation risk premium, are founded on the difference between the correlation among constituents implicit in index options and the actual correlation (Ferrari, Poy and Abate 2019). Previous research[1] has explained the use of the implied correlation as an entry signal as discussed earlier. According to (CBOE 2021) the implied correlation can be calculated as,

$$\rho_t^{Implied} = \frac{\sigma_{I,t}^2 - \sum_{i=1}^{N} w_i^2 \sigma_{i,t}^2}{2\sum_{i=1}^{N-1}\sum_{j>i}^{N} w_i w_j \sigma_{i,t}\sigma_{j,t}} \qquad (4)$$

where $\sigma_{Index,t}$ is the 30-day implied volatility of index options at time t and $\sigma_{i,t}$ is the 30-day implied volatility of individual components options on the i-th constituent at time t, w_i is the weight in the index of the i-th stock, provided in Appendix II. According to (Ferrari, Poy and Abate 2019) the sample correlation can be computed as,

$$\rho_t^{Sample} = \frac{\sum_{i=1}^{N}\sum_{j>i}^{N} w_i w_j \sigma_{i,t}\sigma_{j,t}\rho_{i,j,t}}{\sum_{i=1}^{N}\sum_{j>i}^{N} w_i w_j \sigma_{i,t}\sigma_{j,t}}. \qquad (5)$$

Entry Signal

<u>Implied correlation</u>

This research uses the framework for the entry signal presented by (Ferrari, Poy and Abate 2019). In this framework, a long dispersion trade is opened when the indicator is high, and an opposite position is opened when the indicator is low, i.e.,

$$Indicator_t = \rho_t^{Implied} - \rho_t^{Sample}. \qquad (6)$$

The use of Bollinger bands will indicate when the indicator is considered high and low. The identification of high and low is calculated by using the 30-day moving average and its 1.5 standard deviations. An entry of a trade is considered when the indicator in (6) breaks above the upper band or breaks the lower band of the 1.5 standard deviation. This approach was previously used by Ferrari, Poy and Abate (2019).

<u>Amount Dispersion</u>

The amount of dispersion is calculated as in (3). It signals the difference between at the money implied volatility of the index and the at the money implied volatility of its constituents. A 30-day moving average of the dispersion amount is calculated. From the moving average 1.5 and -1.5 standard deviations are calculated. When the indicator goes

[1] Deng (2008), Ferrari, Poy and Abate (2019) & Schneider and Stubinger (2020)

beyond the 1.5 standard deviations a long dispersion position is taken, when the indicator goes below the -1.5 standard deviations a short dispersion is taken.

Pairwise Correlation signal

The pairwise correlation signal divides the implied volatility of the index (sigma) by the subset of the portfolio with the weights derived from the PCA analysis, with a perfect positive pair-wise correlation. Since the denominator represents the volatility of a portfolio with no dispersion and diversification benefits, the ratio can be interpreted as an inverse measure of the options market's implied dispersion/risk reduction compared to a situation of zero risk reduction as stated by (BSIC n.d.). The lower the signal, the higher the option implied dispersion and the lower the option-implied correlation. Also in this case, the 30-day moving average and its standard deviation are calculated. A long dispersion position is taken when the indicator exceeds 1.5 standard deviations, the opposite position is taken when the indicator drops below -1.5 standard deviations.

PnL

First the PnL (profit and loss) part constructs the portfolio which follows the returns and cumulative returns over time. Straddle positions are taken in order to have a Vega focusing exposure. The strategy buys straddles of the constituents and sells the index when having a long dispersion position. An index straddle is bought and the straddles of the constituents are sold when a short dispersion position is taken. For the first strategy, delta neutrality is not taken into account. The delta of an at the money (ATM) straddle starts with neutral or close to neutral delta. However, as the underlying asset moves, the delta of a straddle position tend to increase or decrease. This will result in a strategy that is prone to idiosyncratic movements of the underlying asset that is in conflict with the main objective of a dispersion strategy, as this strategy focuses on implied volatility. Different strategies can be adopted to maintain a delta neutral position over time. The strategy will be hedged by taking a position in the underlying assets. The focus of this research will purely be based on gaining a pure delta-neutral strategy in addition to a strategy that does not take the delta into account.

In order to evaluate the strategies, different performance metrics are assessed. First, the Sharpe ratio is calculated for the three strategies. According to Israelsen (n.d.) "*the reliability of the Sharpe ratio as an evaluating measure comes into question when excess return, and thus the calculated Sharpe ratio, is negative.*" For this reason, the Sharpe ratio is calculated both with a risk-free rate of 0% and with the 10 years treasury yield. Specifically,

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p}. \qquad (7)$$

Where R_r is the portfolio returns, R_f risk free rate and σ_p volatility (standard deviation) of the portfolio. Beside the Sharpe ratio, the risk adjusted performances of the portfolios are gauged by using $VTI (Vanguard Total Index) as a benchmark with the Capital Asset Pricing Model (CAPM). CAPM describes the relation between returns of the portfolio and systematic risk. The model describes this relation as follow;

$$R_p = \beta R_m + \alpha \qquad (8)$$

Where β represents the systematic risk of the portfolio, R_m the returns of the benchmark ($VTI), R_p portfolio returns and α the excess return.

III. Data

Different data sources are used to assess the dispersion trading strategy. First, the composition of the OEX index is accessed via the Refitinv Eikon. The daily prices of the constituents are extracted via the Refinitiv Eikon API with the program language Python. This dataset has to be cleaned, as the ticker DOW.N includes missing values. DOW Inc (DOW.N) and DOW Inc split from the DowDuPont in 2019 and no price data before 2019 is available for DOW Inc. For this reason, DOW.N is discarded from the composition.

In order to calculate the entry signal the 30 days at the money implied volatility is extracted from Refinitiv Eikon API. Finally, the derivative data is retrieved from the Optionmetrics IvyDB accessed via WRDS. This dataset contains some missing values for the OEX index. For these values, imputation techniques are used. The closest date from the missing objects is taken in order to fill the missing data. With this approach, returns will turn to 0 resulting in a minimum impact on the portfolio's volatility. Transaction costs are influencing the profitability of the strategy. According to Plerou, Gopikrishnan and Stanley (2005) the bid-ask spread and volatility are logarithmically related, in addition, a logarithmic relation holds between transaction-level bid-ask spread and trade size. According to Chordia, Roll and Subrahmanyam (2007) market efficiency is decreasing when the bid-ask spreads are increasing. Interpreting the bid-ask spread is therefore an important factor in constructing the portfolio. The bid-ask spread per individual security is presented in Appendix II. As expected, the bid-ask spread increases during periods of uncertainty. Most of the securities present a jump in the period of March 2020. However, the OEX security shows a higher bid-ask spread during 2021. This is in contrast with the bid-ask spread of the SPX where the bid-ask spread only jumped during March 2020. The abnormal increase of the bid-ask spread could influence the trading strategy; it could increase the performance of the strategy as market inefficiencies will increase and a lower level of liquidity will influence transaction costs negatively. For this reason, the SPX will be taken into account when performing the strategy.

The returns of the SPX are regressed on the returns of the OEX. This will give an overview to which extent the returns of the SPX are explaining the returns of the OEX. As expected, SPX explains the variance of the returns of the OEX adequately with an R-squared of 0.999 and a significant p-value with a 0.01 significance level. For this reason, the OEX could be replaced by the SPX when performing the dispersion trading strategy if the liquidity of the OEX options influences the performance.

IV. Results

Variation Explanation PCA

The first step is to create a subset of the S&P100 constituents. A different period is used to calculate the weights of the subset in order to reduce biases in the model. The variation explanation part is therefore considered the training part of the model. As explained during the model set-up section PCA is used to explain the variation in the index by its constituents. Appendix II visualizes PCA dimensionality reduction of 3 components grouped per sector. This graph gives an overview of how different sectors are clustered due to specific market risks.

In order to assign weight to the subset of the index, a PCA reduction with 7 components is performed. As a result, the analysis has a joint explanation of 93,294%. The 7 components are suitable in this case as the joint explanation is higher than 90%. The constituents are ordered on their weighted mean correlation (Appendix III presents the top 20 weighted mean correlations). These top 20 are regressed without intercept on the index. Discard constituents without a significance of at least 1% and not a negative coefficient as shorting the constituents is a constraint in the model. This is repeated until all factors are satisfied. Results are provided in Table 1. It shows the securities that are signs explaining the index volatility. The coefficients are used as the weights for further calculations for the entry signal construction and the weights for the portfolio.

Ticker	coef	std err	t	P>|t|	[0.025	0.975]
GS	0.0788	0.013	6.187	0	0.054	0.104
UNP	0.0469	0.015	3.116	0.002	0.017	0.076
LIN	0.124	0.015	8.065	0	0.094	0.154
BLK	0.1582	0.015	10.699	0	0.129	0.187
MCD	0.0803	0.016	5.127	0	0.05	0.111
V	0.1354	0.026	5.3	0	0.085	0.186
MA	0.0783	0.021	3.663	0	0.036	0.12
CMCSA	0.111	0.014	8.078	0	0.084	0.138

Table 1 Weights of Subset S&P100

Entry Signal

As stated before, (Deng 2008) provides empirical evidence of the benefits of the use of entry signals. Different entry signals are tested. First, the implied correlation signal previously used by (Ferrari, Poy and Abate 2019) is tested on the data sample.

The implied volatility of the subset is calculated by multiplying the weights as calculated in Table 1 by the 30 days at the money implied volatility (IV) summed over all securities. Figure 1 presents the implied volatility of both the OEX and its subset with the weights from Table 1. Observing the graph, one can clearly see a jump in the IV during March 2020 due to COVID-19 Li (2020) and visually a relatively smaller jump in IV during the American elections of November 2020 Cotoga (2020). In 2021 different events influenced the IV. First at the beginning of January 2021 the capitol attack Ortner (2021) and in the end of January IV climbed due to the implication of the 'Reddit Traders' Nagarajan (2021).

The amount of dispersion is calculated as indicated in (3), as presented in Appendix V the dispersion is influenced severely by the volatility of the market in the period of March 2020 due to the uncertainty raised by COVID-19.

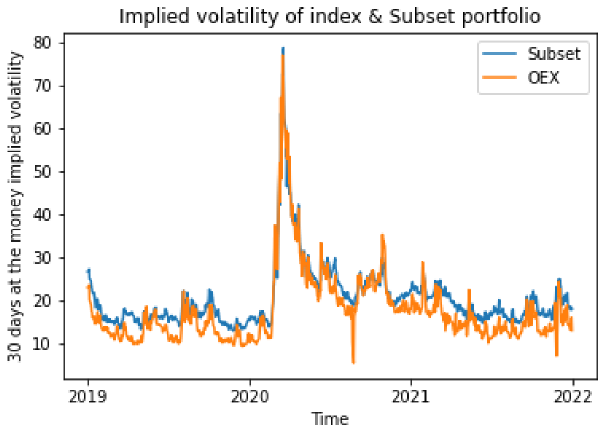

Figure 1 Implied Volatility Index & Subset

Implied Correlation

The entry signal is constructed by the difference in implied correlation and sample correlation. The implied and sample correlation is calculated as indicated in (4) and (5), the difference is calculated by equation (6). Trade is opened when the signal exceeds the 1.5 standard deviations of the 30-day moving average of the indicator. As shown in appendix V in the three year period, 162 entry signals are constructed with 65 long and 97 short positions.

Amount Dispersion

The amount of dispersion is the squared implied volatility of the constituents minus the squared implied volatility of the index as shown in expression (3). Figure 1 presents the implied volatility for the index and its constituents. During the timeframe considered, the implied volatility may deviate from each other, however, during moments of uncertainty, both the implied volatility of the index and its constituents tend to cluster at an equal amount of implied volatility (see Appendix V for the amount of dispersion and its trading signals). In total, 303 entry signals are constructed with 154 long and 149 short positions.

Pairwise Correlation Signal

This deviation and coherence behaviour could be explained by the increased demand of put for hedging. This specific deviation in the implied volatility could be incorporated into a dispersion trading strategy. A long dispersion trade position is taken when the indicator exceeds the 30 day moving standard deviation and vice-versa for the short signal. In total, 329 entry signals are constructed with 165 long and 164 short positions.

Profit and Loss

The returns are calculated for the position that is taken by the entry signal. Vanguard Total Stock Market Index Fund ETF VTI (VTI) is used as a benchmark for the performance metrics. The risk-free rate, the 10 years Treasury yields, is extracted from the Refintiv eikon API.

Cumulative Returns

The cumulative returns are calculated for the different dispersion portfolios and the benchmark (VTI). Figure 2 presents the cumulative returns of the three designated strategies. Both implied correlation and pairwise correlation strategy tend to outperform the VTI benchmark regarding the overall return. All strategies have different periods without any returns. This could occur due to two factors. Markets could be efficient resulting from no trading signal that is occurring during the specific period, or trading opportunities are lacking due to certain restrictions set by only allowing straddles with matching maturity dates and a minimum period of 8 days before maturity.

The dispersion strategy clearly outperforms the benchmark during the period of March 2020. According to Lalwani and Meshram (2020), markets were less efficient during the COVID-19 crisis where dispersion trading strategies could benefit from the net buying pressure and correlation risk premium in the market. During this period volatility spiked resulting in reduced liquidity and an increase in transaction costs.

Another observation from the strategies is the amount of volatility. Currently, the straddles are not rebalanced on a daily basis resulting in a strategy that is not delta neutral, resulting in a portfolio that is prone to price deviations when the underlying asset moves.

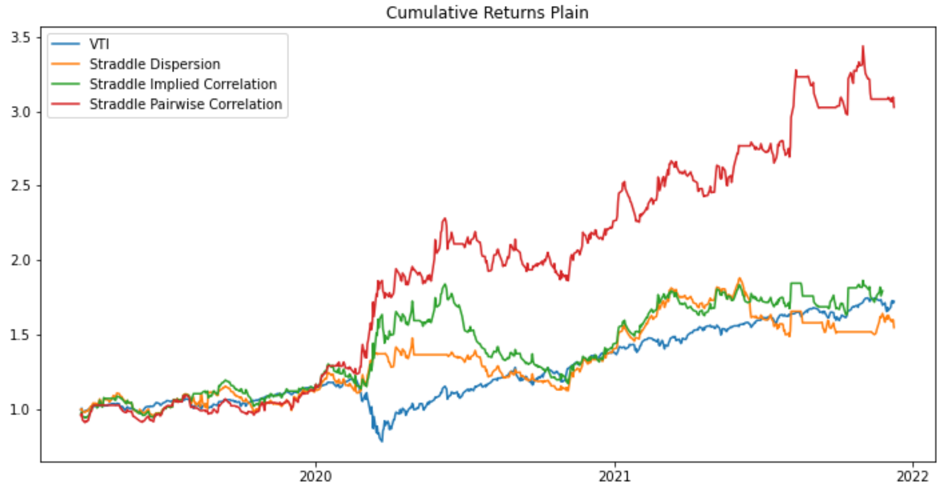

Figure 2 Cumulative Returns Plain

The delta is hedged by taking an equity position in the underlying asset with the equity's weights represented by Delta where selling a straddle will result in short selling the equity position. As shown in Figure 3, the delta-neutrality results in a less volatile portfolio. The annual volatility of the pairwise correlation strategy reduces from 30.04% to 21.99%.

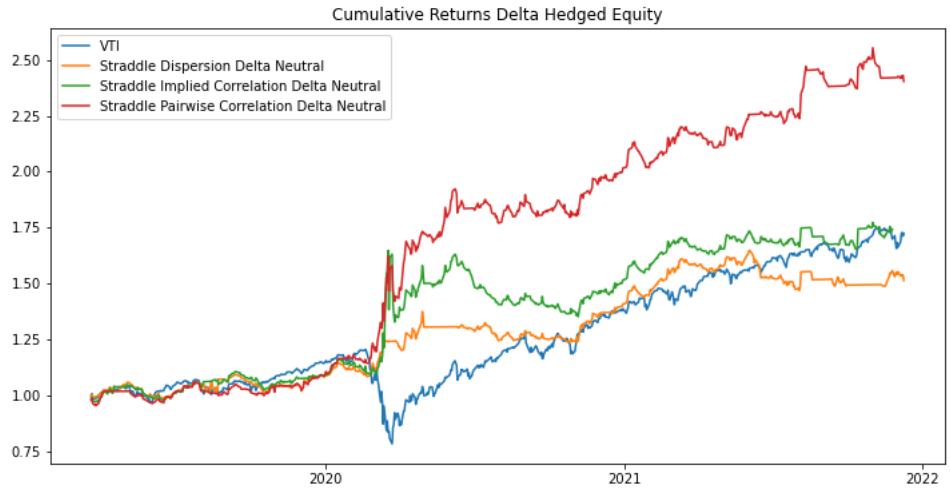

Figure 3 Cumulative Returns Delta Hedged

Performance metrics

The three strategies are tested by the previously defined performance metrics. Annual returns of the best performing strategy, pairwise correlation, is on average 31.87% compared to 25.34% annual returns of VTI during the same period.

The Sharpe ratios are presented in Table 2. As a comparison, the Sharpe ratio of the S&P500 and VTI are 0.32 (source: Bloomberg) and 0.019 respectively. The pairwise correlation strategy represents the best performing strategy with a Sharpe ratio of 0.93 (including the Risk Free Rate).

Strategy	**Sharpe Ratio US10Y**	**Sharpe ratio Rf 0%**
Dispersion Amount	0.014	0.783
Implied Correlation	0.185	0.921
Pairwise Correlation	0.938	1.674
Dispersion Amount Delta Hedged	-0.219	1.197
Implied Correlation Delta Hedged	0.138	0.895
Pairwise Correlation Delta Hedged	0.753	1.760

Table 2 Sharpe ratio

The CAPM in Table 3 describes the relation between the portfolios' returns and its systematic risk. According to the Alpha, the portfolio tended to outperform the market with

0.001. An interesting feature of the CAPM is the beta that is close to zero. The dispersion portfolio is performing independently of the market resulting in low systematic market risk.

Strategy	**alpha**	**beta**	**p-value**
Amount Dispersion	0.001	-0.090	0.007
Implied Correlation	0.001	-0.169	0.000
Pairwise Correlation	0.001	-0.070	0.031
Amount Dispersion Delta Hedged	0.001	-0.171	0.005
Implied Correlation Delta Hedged	0.001	-0.304	0.000
Pairwise Correlation Delta Hedged	0.002	-0.254	0.000

Table 3 CAPM estimation results

V. Conclusion

This research has provided a review of dispersion trading strategies on the S&P100 with different entry signals and has given evidence for the interpretation of mispricing of the index options and its constituents regarding the implied correlation and pairwise correlation. The research showed a simple dispersion trading strategy using at the money straddles on the S&P100 and its components. The strategy has an annual return of 31.87%, in comparison to the 25.34% of the VTI benchmark. The Sharpe ratios are indicating a good return per unit of risk as the best performing strategy has a Sharpe ratio of 0.938 compared to the Sharpe ratio of 0.01 of the VTI benchmark. The CAPM indicates a slight outperformance of the general market with an Alpha of 0.01 and 0.02 while Delta hedged. The beta indicates a strategy not prone to systematic market risks as the beta is slightly negative for the pairwise correlation strategy (-0.17).

The delta neutral strategy uses an equity position in the underlying asset resulting in extra transaction costs and possibilities of slippage (the difference between expected and execution price). The impact of the transaction costs is unknown during the research and could influence the excess returns of the strategy. The period of the execution of trades is from 2019 until 2021 when the COVID-19 crash had a significant impact on the market. During this period, volatility spiked resulting in market inefficiencies and liquidity problems adding to an increase in transaction costs. An optimized hedge could be realised by rebalancing the straddles to at the money straddles on a daily basis resulting in a delta-neutral and Vega rich portfolio and reduced transaction costs.

Therefore, the analysis provides evidence that inefficiencies are occurring providing arbitrage trading opportunities.

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Appendix

<u>Appendix List:</u>

I. Table 1 previous studies
II. Bid-Ask spread
III. PCA plot
IV. Top 20 weighted mean correlation
V. Entry Signals

Appendix I

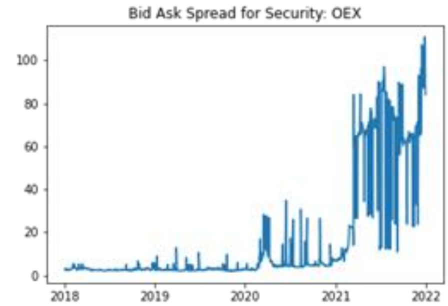
Table 1

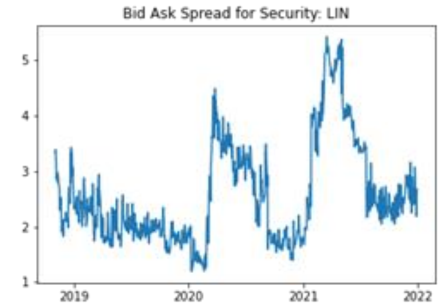
Research	Type of Strategy	Returns	Sharpe ratio
(Ferrari, Poy and Abate 2019)	*	9.42%	2.47
(Schneider and Stubinger 2020)	PCA Straddle Delta Hedged*	18.41%	0.5157
(Schneider and Stubinger 2020)	PCA Straddle Delta unhedged*	29.88%	0.3897
(Schneider and Stubinger 2020)	Largest constituents straddle Delta hedged*	4.01%	0.0599
(Schneider and Stubinger 2020)	Largest constituents straddle delta unhedged*	10.49%	0.1334
(Schneider and Stubinger 2020)	Market	3.47%	0.0890
(Buraschi, Trojani and Vedolin, Equilibrium Index and Single-Stock Volatility Risk Premia 2009)	*	19,47%	Unkown
(Deng 2008)	Implied & Historical correlation	12.7%	0.70
(Deng 2008)	Implied correlation GARCH forecast	14%	0.79
(Deng 2008)	Delta-hedged dispersion	15.2%	0.89
(Deng 2008)	Dispersion based on PCA	15.2%	0.69
(Deng 2008)	Trading OTM index Strangles	10%	0.89

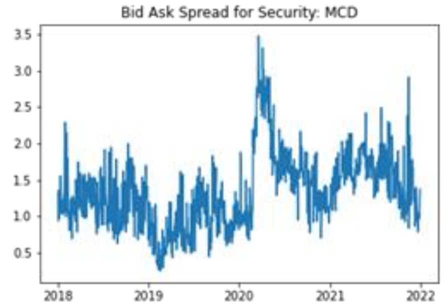
*Before transaction costs

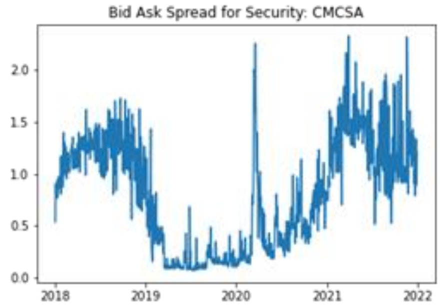
Appendix II

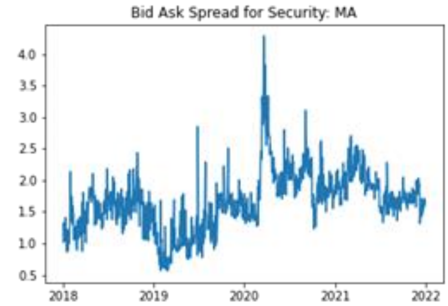
Bid-Ask Spread

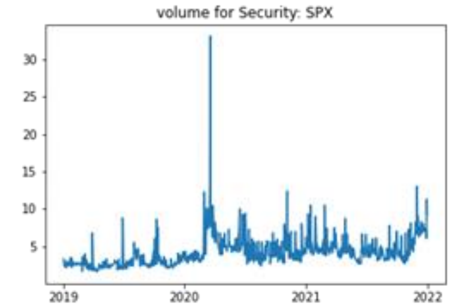


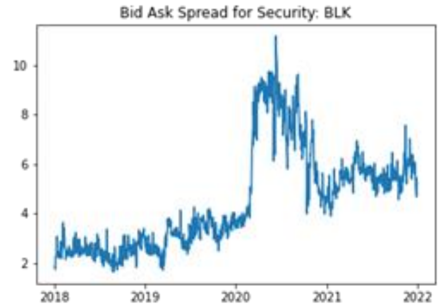






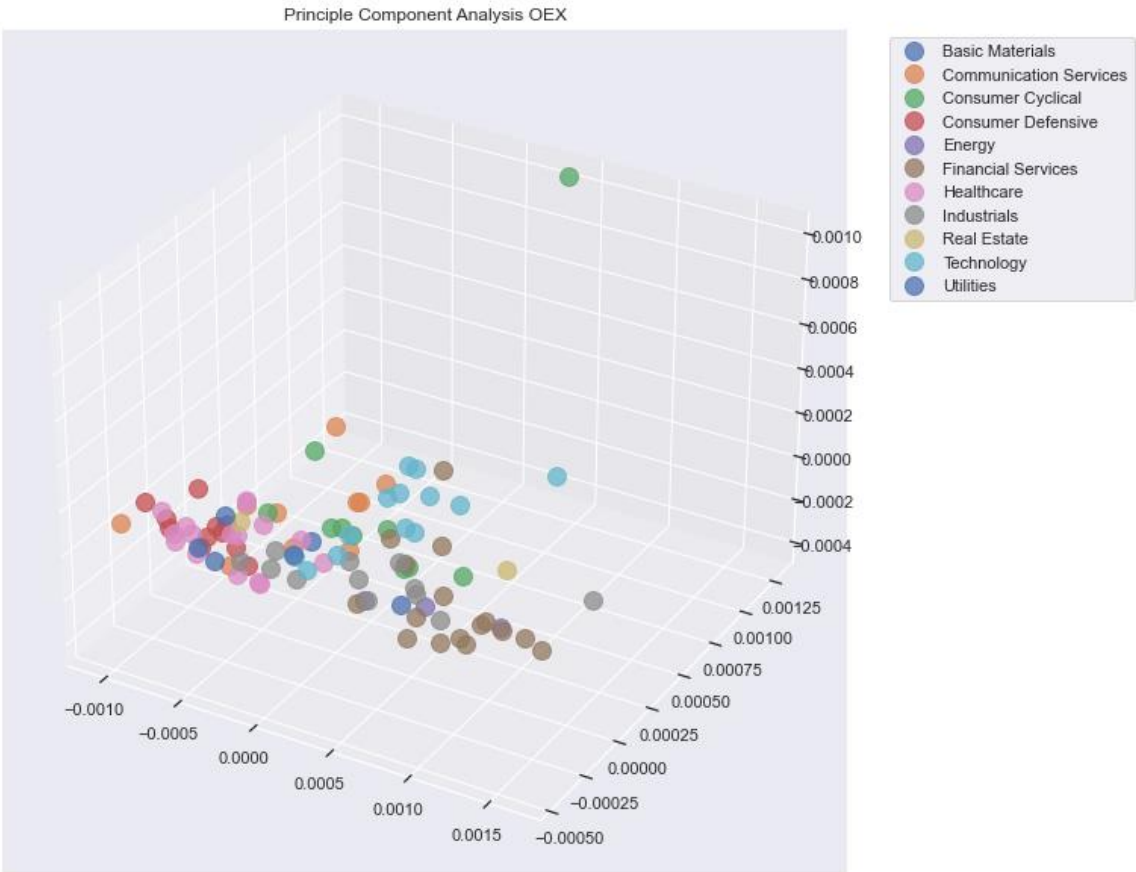






Appendix III

PCA Plot

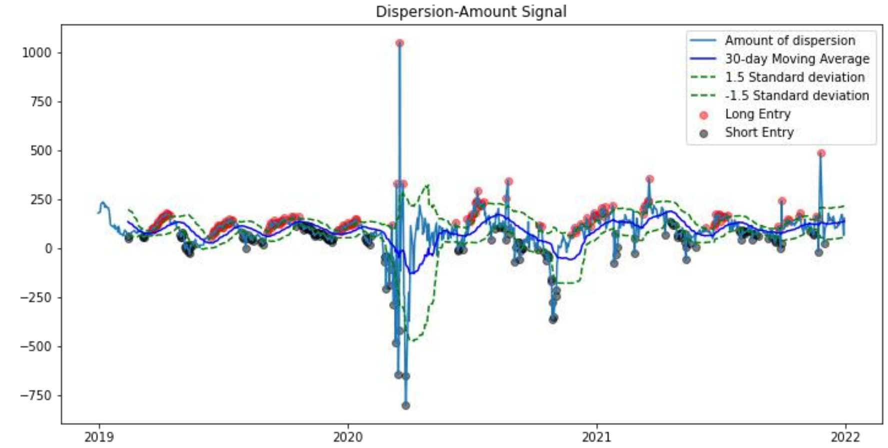


Appendix IV Top 20 weighted mean correlation

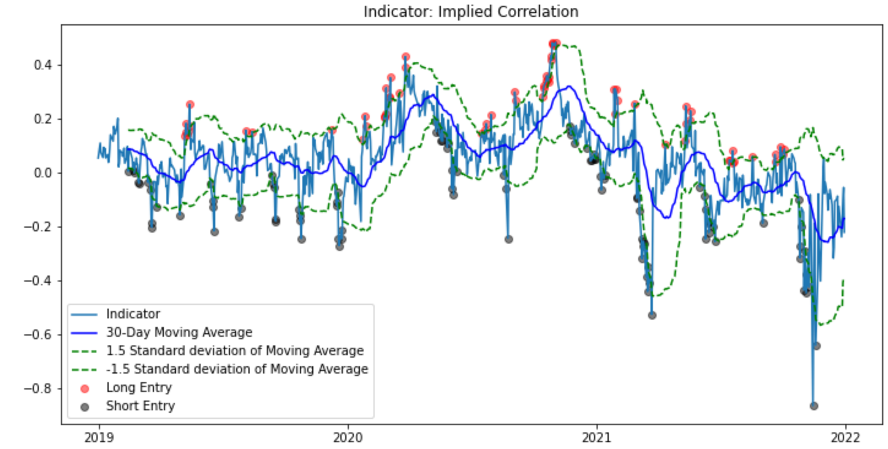
Ticker	Weighted Mean Correlation
C	0.695135161
COF	0.693069849
AXP	0.690797669
HON	0.689536909
GS	0.688036891
MS	0.685666278
JPM	0.683217289
EMR	0.681265989
MET	0.68043409
AIG	0.680177726
BAC	0.676019209
RTX	0.674040169
UNP	0.664540539
WFC	0.657427211
BK	0.656493197
USB	0.654972724
GM	0.654656924
CVX	0.653389688
GD	0.650189412
XOM	0.642464358
BA	0.640963919
DD	0.63570656
DIS	0.634683289
CAT	0.634334096
BKNG	0.63388569
MDT	0.633729476
COP	0.631616132
IBM	0.624943281
SPG	0.619955574
LIN	0.619827941
BLK	0.618064412
F	0.613768859
GE	0.601876758
SBUX	0.588900351
MMM	0.580469196
MCD	0.565969206
V	0.54588306
MA	0.542808303
CMCSA	0.542323446
T	0.539647814

Appendix V

Entry Signals Dispersion



Entry Signal Implied Correlation



Entry Signal Pairwise Correlation