



August 1, 2017

Brent J. Fields  
Secretary  
U.S. Securities and Exchange Commission  
100 F Street, NE  
Washington DC 20549-1090

**RE: Notice of Filing of a Proposed Rule Change to Permit the Listing and Trading of Managed Portfolio Shares; and to List and Trade Shares of the Following Under Proposed Rule 14.11(k): ClearBridge Appreciation ETF; ClearBridge Large Cap ETF; ClearBridge MidCap Growth ETF; ClearBridge Select ETF; and ClearBridge All Cap Value ETF [Release No. 34-81247; File No. SR-BatsBZX-2017-30]**

Dear Mr. Fields,

I am writing the U.S. Securities and Exchange Commission (the “Commission”) with regard to the Commission’s July 28, 2017 filing notice pertaining to the proposed rule change application submitted on June 1, 2017 by Bats BZX Exchange, Inc. (the “Exchange”).<sup>1, 2, 3</sup> In addition to the proposed rule change, the Exchange wishes to list and trade the ClearBridge Appreciation ETF, the ClearBridge Large Cap ETF, the ClearBridge MidCap Growth ETF, the ClearBridge Select ETF and the ClearBridge All Cap Value ETF, non-transparent exchange traded funds<sup>4</sup> which will operate using intellectual property developed by Precidian Investments LLC (“Precidian”) and which are described in a Form N-1A Registration Statement filed on April 4, 2017 by Precidian ETF Trust II (the “Registration Statement”).<sup>5</sup>

The rule change filing by the Exchange and the Registration Statement both rely on representations of fact and statistical analyses pertaining to the intellectual property developed by Precidian that is documented in a second amended application for exemptive relief prepared by Precidian ETFs Trust

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<sup>1</sup> See <https://www.sec.gov/rules/sro/batsbzx/2017/34-81247.pdf> (Release No. 34-81247; File No. SR-BatsBZX-2017-30)

<sup>2</sup> See <https://www.sec.gov/rules/sro/batsbzx/2017/34-80911.pdf> (Release No. 34-80911; File No. SR-BatsBZX-2017-30)

<sup>3</sup> As background, I am the founder of Blue Tractor Group, LLC, which on July 31, 2017 filed a third amended application for exemptive relief with the Commission for the Shielded Alpha™ ETF structure. I am a graduate of the University of London (mathematics) in England and have worked and consulted for over 30 years in both England and United States for many financial institutions, primarily developing and constructing quantitative models related to alpha generation and risk management. I am the sole inventor of the methods and ideas underpinning the Shielded Alpha™ ETF structure, which is completely different concept to a non-transparent exchange traded fund. See <https://www.sec.gov/Archives/edgar/data/1668791/000168035917000403/bluetractor40app7312017.htm> (File No. 812-14625)

<sup>4</sup> Precidian’s proposed exchange traded fund structure is a non-transparent fund because no actual portfolio holdings are disclosed daily and the market will only know the holdings on a quarterly basis. It is perplexing to hear Precidian’s principals now refer to the product as a semi-transparent exchange traded fund versus a non-transparent exchange traded fund as they did so in the past – what additional portfolio information is being disclosed?

<sup>5</sup> See [https://www.sec.gov/Archives/edgar/data/1701878/000114420417018966/v463050\\_n1a.htm](https://www.sec.gov/Archives/edgar/data/1701878/000114420417018966/v463050_n1a.htm) (File No. 811-23246)

and Precidian Funds LLC that was filed with the Commission on September 21, 2015.<sup>6</sup> Note that this filing was amended a third time by Precidian ETFs Trust, Precidian ETF Trust II and Precidian Funds LLC and was re-filed with the Commission on May 2, 2017.<sup>7</sup>

Of particular note are two statistical studies prepared by Dr. Ricky Alyn Cooper and presented as appendices in both filings that purport to demonstrate that reverse engineering of the undisclosed portfolio by a predatory third party is ‘rather unlikely’. The two statistical studies appended to the May 2, 2017 filing are identical to the ones appended to the September 21, 2015 filing (see Reverse Engineering section below).

The Commission in its July 28, 2017 notice stated that it designated September 17, 2017 as the date whether it will approve, disapprove or institute proceedings to determine whether to disapprove the proposed rule change by the Exchange. To that end I wish to make the following observations known to the Commission in advance of September 17, 2017. It is my view that the proposed actively managed non-transparent exchange traded fund structure developed by Precidian does not meet the statutory standard that approval is necessary or appropriate in the public interest and consistent with the protection of investors.

I have prepared comments that are focused on key areas where I believe the proposed structure is significantly flawed, these include: (1) *Reverse Engineering*, (2) *Hedging*, (3) *Portfolio Content Security*, (4) *Pricing* and (5) *Violation of Federal Securities Law*.

### **(1) Reverse Engineering**

With respect to the application for exemptive relief filed by Precidian on May 2, 2017, I wish to provide the Commission my observations concerning **Appendix E**, entitled “**Additional Research on the Ability to Reverse Engineer the Proposed Precidian ETF**” (pages 78 – 82). The statistical analysis in Appendix E was prepared in August 2015 by Dr. Ricky Alyn Cooper from the Illinois Institute of Technology – Stuart School of Business and to my knowledge has not been updated. The August 2015 filing from Dr. Cooper with the Commission was in response to questions the Commission had with an earlier July 2015 analysis Dr. Cooper undertook on behalf of Precidian. The July 2015 analysis has also been submitted as Appendix C in the May 2, 2017 filing (pages 59 – 66). My comments in this section however are restricted to a review of Appendix E.

I have however addressed Dr. Cooper’s July 2015 study (Appendix C) by way of a July 17, 2017 report prepared by Dr. Anthony Hayter from the University of Denver’s Department of Business Information and Analytics. Dr. Hayter’s conclusions completely refute the contention of Dr. Cooper that reverse engineering the unknown portfolio is not feasible - see Appendix One to this letter.

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<sup>6</sup> See [https://www.sec.gov/Archives/edgar/data/1396289/000114420415055774/v420579\\_40appa.htm](https://www.sec.gov/Archives/edgar/data/1396289/000114420415055774/v420579_40appa.htm) (File No. 812-14405)

<sup>7</sup> See [https://www.sec.gov/Archives/edgar/data/1396289/000114420417024016/v465816\\_40appa.htm#\\_045](https://www.sec.gov/Archives/edgar/data/1396289/000114420417024016/v465816_40appa.htm#_045) (also File No. 812-14405)

Dr. Cooper's August 2015 study offers additional statistical evidence that he claims bolster his contention from the July 2015 study that it is 'rather unlikely' that the undisclosed portfolio under the Precidian methodology could be reverse engineered by a predatory third party.

His mathematical argument in Appendix E in part hinges on the frequency of dissemination of the verified intra-day indicative value ("VIIV") increasing from 15 seconds to 1 second intervals. The reason this is important is that the VIIV will be calculated using the weightings and holdings of the actual portfolio.

Dr. Cooper observes<sup>8</sup>:

*"Although the correlation improves with lower frequency estimation windows, it does not follow that one could reverse engineer the underlying portfolio. This follows because lower frequency data does not have enough observations per day to effectively achieve this task...."*

and thereafter concludes<sup>9</sup>:

*"The reporting mechanism of Precidian reduces the correlation of the reported price quotes each second and the corresponding unscaled prices to .33, based on our **stylized methodology** [emphasis added] as described in Cooper (2015). This reduction in correlation is the primary factor that prevents the reverse engineering of the ETF's positions in the underlying stocks even after ten days of unchanging weights;"*

As the Commission is aware, the **stylized methodology** referenced above refers to certain structuring proposals for Precidian's non-transparent exchange traded product that were first described by Dr. Cooper in his July 2015 study (Appendix C) and then expanded upon by Precidian in the September 21, 2015 and May 2, 2017 filings:

- i. Scaling the ETF to an initial value of \$20.00 and allowing it to range to no greater than \$60.00 before undertaking a stock split to bring it back down to \$20.00;
- ii. Calculating the VIIV using input prices that are the midpoint of the bid-ask for the portfolio constituents; and
- iii. Truncating the value of the disseminated VIIV to two decimal places.

Dr. Cooper and Precidian claim that the **stylized methodology** will prevent reverse engineering of the underlying portfolio by predatory market participants.

However, examination of the parameters Dr. Cooper employed in his August 2015 study leads to a totally opposite conclusion.

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<sup>8</sup> Appendix E, page 81

<sup>9</sup> Appendix E, page 81

### **Part I: Correlations Materially Increase when there is Higher Volatility**

Dr. Cooper informs the reader that as the frequency of the disseminated VIIVs increases from 15-second to 1-second intervals, the reduction in volatility, because of re-scaling and decimal truncation, lowers the correlation between the VIIV price and the actual underlying NAV of the ETF and prevents reverse engineering.

To reiterate, his conclusion stated that:<sup>10</sup>

*“This reduction in correlation is the primary factor that prevents the reverse engineering of the ETF’s positions in the underlying stocks even after ten days of unchanging weights.”*

**Therefore, the logical caveat is that if one increases the level of correlation then reverse engineering will become possible, despite the stylized methodology proposed by Dr. Cooper and Precidian.**

This can be demonstrated to be readily feasible by a motivated predatory third party. Our analysis consisted of:

1. The construction at 1-second intervals of a random time series of NAVs and indexing the first value to 1.0;
2. Multiply the indexed NAV time series by 20, 30, 40, 50 and 60 so that the start-of-day value will be \$20.00, \$30.00, \$40.00, \$50.00 and \$60.00. Term the re-scaled NAV time series the Rescaled NAV;
3. Generate an additional time series to represent the disseminated VIIVs. This was undertaken by truncating the time series of rescaled NAVs to 2-decimal places; and
4. Calculate a time series of returns for both the NAV and VIIV time series. The correlation between both time series of returns is then reported.

Note that since the initial NAV time series is assembled at 1-second intervals over a 6.5-hour trade day that there are 23,400 observations for this correlation exercise.

The level of market risk, or volatility, used to generate the time series of NAV returns is represented by ‘ $k\sigma$ ’, where  $k$  is a constant and  $\sigma$  is the average daily volatility for the S&P 500. So, if  $\sigma$  is the average daily volatility than  $0.5\sigma$  is half the daily average and  $2\sigma$  is twice the daily average etc.

The level of market risk at the start of the analysis was set to resemble that used by Dr. Cooper in his study. Specifically, for a market risk level of  $0.5\sigma$  and for the rescaled & rounded \$20.00 NAV time series, the correlation between the NAV & VIIV returns over the trade day was 36.36% as compared to Dr. Cooper’s value of 33%. Note that the level of market risk chosen by Dr. Cooper in his study (approximately  $0.5\sigma$ ) is ‘on the low side’, especially given that he only used this one level throughout his analysis and did not examine higher market volatility.

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<sup>10</sup> Appendix E, page 81

The table below displays the correlations between the NAV and VIIV returns as both market risk (volatility) and the re-scaled NAV increases. Even at the initial market risk level of  $0.5\sigma$  and with the same set of second-by-second returns, as the re-scaled value increases to \$30.00 the correlation moves to 45.35% and when its \$60.00 the correlation reaches 64.05%. The higher correlation is because of more movement (or volatility) in the VIIV return series, despite the stylized methodology.

CORRELATION OF VIIV VERSUS NAV AT INCREASING MARKET RISK AND INCREASING NAV										
	0.5 $\sigma$	$\sigma$	1.5 $\sigma$	2 $\sigma$	2.5 $\sigma$	3 $\sigma$	3.5 $\sigma$	4 $\sigma$	4.5 $\sigma$	5 $\sigma$
\$20.00	36.36%	52.27%	64.23%	73.31%	79.67%	84.68%	88.67%	90.82%	92.25%	94.16%
\$30.00	45.35%	63.75%	77.40%	85.29%	89.21%	92.36%	94.37%	95.66%	96.39%	97.26%
\$40.00	52.65%	73.36%	85.24%	90.89%	93.60%	95.44%	96.71%	97.46%	97.91%	98.42%
\$50.00	58.63%	80.26%	89.66%	93.78%	95.67%	97.02%	97.88%	98.33%	98.62%	98.99%
\$60.00	64.05%	84.89%	92.54%	95.50%	96.88%	97.91%	98.52%	98.83%	99.04%	99.29%

As one assumes an increase in market risk up to  $\sigma$  and then up to  $5\sigma$  then the correlations between VIIV and NAV dramatically increase. For any given level of NAV rescaling, as the market volatility increases so does the level of correlation between the VIIV and the actual NAV returns and the correlation increase is marked.

The increased correlations unequivocally demonstrate that information content within the VIIV series increases as the NAV increases, despite the stylized methodology. Dr. Cooper stated that low correlation prevents reverse engineering. Therefore using Dr. Cooper’s own metric, it follows that with high correlation a predatory third party will be able to reverse engineer the portfolio.

**Part II: Higher Correlation Along with a Greater Number of Observations is Readily Obtainable**

Dr. Cooper further observes that:<sup>11</sup>

*“At lower frequencies the correlations improve. For example, at a one minute reporting period, the correlation improves to .85. At a 30 minute reporting period, the correlation improves further to .98. Thus, at for any period outside of the realm of ultra-high frequency, the movements in the scaled price are very highly correlated with the movements in the unscaled price. Although the correlation improves with lower frequency estimation windows, it does not follow that one could reverse engineer the underlying portfolio. This follows because lower frequency data does not have enough observations per day to effectively achieve this task.”*

So, Dr. Cooper confirms that as the frequency of dissemination of the VIIVs decreases (i.e. from 1-second back up to 15-second intervals, or even at every 1 minute, every 30 minutes etc.) the correlation between the VIIV and actual NAV significantly increases. His own data shows a correlation of 85% at 1-minute and 98% at 30-minute intervals. But, he says reverse engineering is still not possible because despite the very high correlations at low frequencies, the number of actual observations is not enough. In other words, instead of having 23,400 observations using a 1-second

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<sup>11</sup> Appendix E, page 81

interval over a 6.5-hour trading day, with a 1-minute interval the number of observations decreases to 390 and with a 30-minute interval the observations can only number 13.

**Therefore, the logical caveat is that if one increases the number of observations, while maintaining high correlations, then reverse engineering will be possible despite the stylized methodology proposed by Dr. Cooper and Precidian.**

The analysis below demonstrates this also to be readily feasible. In which case, the rationale behind Precidian's filing for the proposed structure must be questioned.

Similar to Part I, a VIIV time series is generated using the re-scaled NAV time series. The only difference is that while in Part I the time series were generated only on a 1-second basis (23,400 observations per trade day), in Part II they are additionally derived using 1-second observations, at intervals of 15 seconds (1,560 observations), 30 seconds (780 observations), 45 seconds (520 observations) and at 1 minute (390 observations).

Correlations are again calculated at the same range of market risk ( $\sigma$ ) used in Part I.

See the data table on following page.

CORRELATION OF VIIV VERSUS NAV AT INCREASING MARKET RISK & NAV AND DECREASED REPORTING FREQUENCY						
	Reporting Frequency	1 second	15 seconds	30 seconds	45 seconds	1 minute
	<i>Observations per Trade Day</i>	<i>23,400</i>	<i>1,560</i>	<i>780</i>	<i>520</i>	<i>390</i>
<b>0.5σ</b>	\$20.00	36.82%	71.28%	82.72%	86.57%	91.24%
<b>0.5σ</b>	\$30.00	45.49%	82.67%	89.99%	93.20%	95.32%
<b>0.5σ</b>	\$40.00	52.36%	89.65%	94.22%	96.66%	97.06%
<b>0.5σ</b>	\$50.00	58.62%	93.17%	96.48%	97.66%	98.09%
<b>0.5σ</b>	\$60.00	63.69%	94.71%	97.43%	98.31%	98.78%
<b>σ</b>	\$20.00	52.96%	89.87%	94.35%	96.13%	96.85%
<b>σ</b>	\$30.00	64.16%	95.15%	97.62%	98.33%	98.73%
<b>σ</b>	\$40.00	73.08%	97.11%	98.56%	99.09%	99.19%
<b>σ</b>	\$50.00	79.84%	98.23%	99.10%	99.39%	99.54%
<b>σ</b>	\$60.00	84.83%	98.83%	99.36%	99.60%	99.65%
<b>1.5σ</b>	\$20.00	64.90%	95.45%	97.24%	98.22%	98.73%
<b>1.5σ</b>	\$30.00	78.02%	97.94%	98.85%	99.25%	99.49%
<b>1.5σ</b>	\$40.00	85.59%	98.84%	99.35%	99.53%	99.67%
<b>1.5σ</b>	\$50.00	89.95%	99.28%	99.58%	99.72%	99.81%
<b>1.5σ</b>	\$60.00	92.70%	99.46%	99.71%	99.80%	99.85%
<b>2σ</b>	\$20.00	72.67%	97.15%	98.62%	98.98%	99.29%
<b>2σ</b>	\$30.00	84.15%	98.67%	99.32%	99.53%	99.69%
<b>2σ</b>	\$40.00	90.33%	99.28%	99.65%	99.74%	99.82%
<b>2σ</b>	\$50.00	93.42%	99.52%	99.77%	99.80%	99.89%
<b>2σ</b>	\$60.00	95.31%	99.66%	99.85%	99.86%	99.92%
<b>2.5σ</b>	\$20.00	80.89%	98.46%	99.14%	99.47%	99.58%
<b>2.5σ</b>	\$30.00	90.14%	99.31%	99.62%	99.77%	99.82%
<b>2.5σ</b>	\$40.00	94.10%	99.60%	99.79%	99.85%	99.89%
<b>2.5σ</b>	\$50.00	96.04%	99.74%	99.86%	99.91%	99.93%
<b>2.5σ</b>	\$60.00	97.19%	99.80%	99.91%	99.93%	99.95%

Note that the 1-second data column is effectively the same analysis that was carried out in Part I.

The data clearly shows that for any given price level, the correlations significantly increase as one moves from the highest (1 second) to the lowest (1 minute) reporting frequency.

This is completely consistent with the observations by Dr. Cooper. However, unlike Dr. Cooper this analysis did not report at frequencies beyond 1 minute. Why bother reporting the correlation at 30 minutes (98%) if the number of observations is so low (13), so as to make reverse engineering impossible. Instead, using a spread between 1 second and 1-minute results in thousands of observations per trading day at correlations far in excess of 90% and in many instances greater than 99%.

The only conclusion can be that with high correlations and a multitude of observations, reverse engineering is indeed possible. The stylized methodology has again done nothing to materially hinder generation of data with high correlation between the VIIV and actual NAV return series.

Additional data generated at higher market risk reaffirms the observation from the analysis in Part I that higher market risk improves correlations – see table below.

CORRELATION OF VIIV VERSUS NAV AT INCREASING MARKET RISK & NAV AND DECREASED REPORTING FREQUENCY						
	Reporting Frequency	1 second	15 seconds	30 seconds	45 seconds	1 minute
	Observations per Trade Day	23,400	1,560	780	520	390
3σ	\$20.00	85.25%	98.83%	99.44%	99.62%	99.74%
3σ	\$30.00	92.57%	99.47%	99.76%	99.84%	99.90%
3σ	\$40.00	95.61%	99.71%	99.86%	99.89%	99.93%
3σ	\$50.00	97.14%	99.80%	99.90%	99.94%	99.95%
3σ	\$60.00	97.97%	99.85%	99.93%	99.95%	99.96%
3.5σ	\$20.00	88.44%	99.13%	99.55%	99.69%	99.76%
3.5σ	\$30.00	94.28%	99.59%	99.79%	99.85%	99.90%
3.5σ	\$40.00	96.67%	99.77%	99.88%	99.92%	99.94%
3.5σ	\$50.00	97.80%	99.86%	99.92%	99.94%	99.96%
3.5σ	\$60.00	98.46%	99.90%	99.94%	99.96%	99.97%
4σ	\$20.00	90.08%	99.24%	99.59%	99.74%	99.78%
4σ	\$30.00	95.21%	99.65%	99.84%	99.88%	99.91%
4σ	\$40.00	97.26%	99.81%	99.89%	99.94%	99.95%
4σ	\$50.00	98.18%	99.87%	99.93%	99.95%	99.96%
4σ	\$60.00	98.73%	99.91%	99.95%	99.97%	99.97%
4.5σ	\$20.00	92.11%	99.43%	99.69%	99.78%	99.84%
4.5σ	\$30.00	96.26%	99.72%	99.86%	99.90%	99.93%
4.5σ	\$40.00	97.83%	99.85%	99.92%	99.94%	99.96%
4.5σ	\$50.00	98.61%	99.90%	99.94%	99.96%	99.97%
4.5σ	\$60.00	99.02%	99.93%	99.96%	99.97%	99.98%
5σ	\$20.00	94.11%	99.58%	99.77%	99.84%	99.87%
5σ	\$30.00	97.19%	99.80%	99.89%	99.93%	99.95%
5σ	\$40.00	98.41%	99.88%	99.94%	99.96%	99.97%
5σ	\$50.00	98.98%	99.93%	99.96%	99.97%	99.98%
5σ	\$60.00	99.29%	99.95%	99.97%	99.98%	99.98%

This analysis provides conclusive evidence that the information content contained within the re-scaled and rounded NAV (i.e. the VIIV), using the **stylized methodology** does not remain *de minimis* and constant, but rather significantly increases as either the underlying NAV and/or market volatility increases. This facilitates high correlations, as demonstrated, between the disseminated VIIV and the underlying fund NAV, providing predatory market participants with the information required to reverse engineer the portfolio to the detriment of fund shareholders.

To further examine the consistency of these results, Blue Tractor Group commissioned a report by Dr. Anthony Hayter from the University of Denver’s Department of Business Information and Analytics (see Appendix One attached).

Dr. Hayter’s July 2017 report examines the two analyses prepared by Dr. Cooper and he undertook simulations. He concludes, *“The simulations presented in this report demonstrate that the reverse engineering of a portfolio is achievable with a substantial degree of accuracy. Obviously, the amount of “shielding” of the portfolio price through scaling and rounding of its value directly affects the accuracy of the reverse engineering. In addition, the information available from the 15-second reporting of real stock prices rather than the simulated stock prices considered in this report may affect*



*the accuracy of the reverse engineering. However, for the realistic scenarios considered in this report it is clear that the reverse engineering of a portfolio is achievable with a substantial degree of accuracy.”*

## **(2) Hedging**

Without knowledge of the underlying stocks comprising the actual fund, under the proposed structure market makers could be exposed to potentially significant and unknown risks. Indeed, without knowledge of the constituents even a 1-second interval correlation of 0.33<sup>12</sup> as illustrated by Dr. Cooper does not mean market makers can effectively hedge the risk inherent in the ETF share. For example, if there is a high cross-sectional correlation across the manager’s investable universe, in such an instance the market maker could be totally unaware that he is taking on potentially high levels of individual stock specific risk as he would be unable to differentiate between two highly correlated stocks.

This level of uncertainty will result in (1) wider and more persistent spreads as market makers seek additional compensation for carrying significant unknown risks or (2) market makers leaving the market altogether as they deem holding the ETF shares ‘too risky’.

Additionally, market makers that hedge at very high frequencies, i.e. millisecond, will consider even 1-second data stale. Asking market makers to conduct their operations up to 1,000 times slower than what many currently do through a Trusted Advisor could potentially exclude them from the market altogether as their inventory and hedging positions cannot be contemporaneously updated.

## **(3) Portfolio Content Security**

Key to the proposed structure is the concept of ‘confidential portfolio information’ remaining secure. Although each Trusted Advisor will be required to sign a NDA there is no mention as to how and who will police this agreement. If a breach of confidentiality is deemed to have occurred, will anyone indemnify investors against any losses incurred as a result of the said breach?

Under the proposed structure confidential portfolio information will be transmitted on a daily basis by the fund custodian to a Trusted Advisor that will interact with an authorized participant and other market participants. This raises security issues.

Precidian in its May 2, 2017 filing did not address issues relating to eavesdropping on communications or data corruption between the fund custodian and the Trusted Advisor. Nor does the most recent filing provide details concerning the proposed operational procedures to keep that confidential information secure with the Trusted Advisor.

How will security policies be implemented to keep the confidential information away from (1) unauthorised personnel, (2) contractors (3) a disgruntled employee or (4) friends & colleagues during

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<sup>12</sup> Appendix E, page 81

casual discussions? It is important to recognise that the confidential portfolio information is contained within the heads of people who have access to it and with human nature being what it is, some will try and profit from that information. Indeed, these risks are real and can be evidenced by recent press releases issued by the Commission:

1. On July 12, 2017, the Commission issued a press release relating to insider trading charges being brought against an individual who “...loaded up on stocks and options in advance of two corporate acquisitions late last year based on confidential information **obtained from his wife** [emphasis added]...”<sup>13</sup>
2. On May 24, 2017, the Commission issued a press release relating to the filing of charges “...in an alleged insider trading scheme involving tips of non-public information about government plans to cut Medicare reimbursement rates, which affected the stock prices of certain publicly traded medical providers or suppliers.” The individual charged allegedly “...obtained key confidential details about upcoming decisions by the Centers for Medicare and Medicaid Services (CMS) **from his close friend and former colleague at the agency** [emphasis added]...”<sup>14</sup>

Furthermore, since the companies who will act as the Trusted Advisor all have emergency off-site back-up systems, how will the confidential portfolio information remain secure at these locations?

In all likelihood, each Trusted Advisor will have its own security, information and auditing procedures. The recent filing provided no details concerning how the funds will audit the capabilities of the Trusted Advisor in order to review their procedures in order to understand any vulnerabilities and thereafter what actions they will take to address those vulnerabilities.

Finally, the recent filing also fails to address the possibility of Trusted Advisor employees copying confidential portfolio information onto laptops for ‘home use’. Such usage raises serious security concerns e.g. loss of the laptop, screen information displayed in public areas etc.

#### **(4) Pricing**

The proposed structure will disseminate the VIIV at a frequency of 1-second. With the financial markets becoming ever more automated how can per second pricing do anything but have a detrimental effect upon market efficiency considering that high frequency trading is carried out in milliseconds. And just how big a negative impact will it have?

The proposed structure sees a pricing verification agent monitor a number of price feeds for both consistency and reliability. What has not been addressed is a potential failure of the pricing verification agents’ systems. If such a failure occurs who will provide monitoring and who will be liable

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<sup>13</sup> See <https://www.sec.gov/news/press-release/2017-125>

<sup>14</sup> See <https://www.sec.gov/news/press-release/2017-109>

for any losses incurred by market participants resulting from an inability to disseminate the VIIV pricing?

The U.S. capital markets have from time to time experienced power failures and technical glitches and the proposed structure does not provide for contingency plans relating to market operations in light of system failures. For example, on August 22, 2013 the Nasdaq Exchange halted trading for 3 hours<sup>15</sup> and as recently as July 8, 2015 the New York Stock Exchange experienced a 4-hour trading blackout.<sup>16</sup> How will pricing, arbitrage and hedging continue if a similar experience was encountered at a Trusted Agent, pricing verification agent or even a pricing source.

It should be recognised that during the more recent NYSE trading blackout, transparent ETF activity carried on pretty much unabated; this was possible because market makers knew the holdings in the underlying index. This would not be possible under the proposed structure.

Key to the proposed structure is the role of the pricing verification agent. Given that system failures can arise at any time and through the most unexpected means (e.g. it was a rodent chewing through a cable that caused the Nasdaq to lose power in the past), not having a contingency plan must be considered an oversight of responsibility.

#### **(5) Violation Of Federal Securities Law**

The proposed structure necessitates that confidential portfolio information be transmitted to the Trusted Agent on a daily basis who thereafter may conduct market trading operations on behalf of authorised participants and other arms-length market participants. This is a clear violation of Federal Securities Law and the Commission has previously expressed its concern relating to parties trading on selective non-public information.

\*\*\*\*\*

Thank you in advance for your consideration of my commentary. I welcome any questions the Commission may have as a result and can be reached at [REDACTED].

Sincerely,

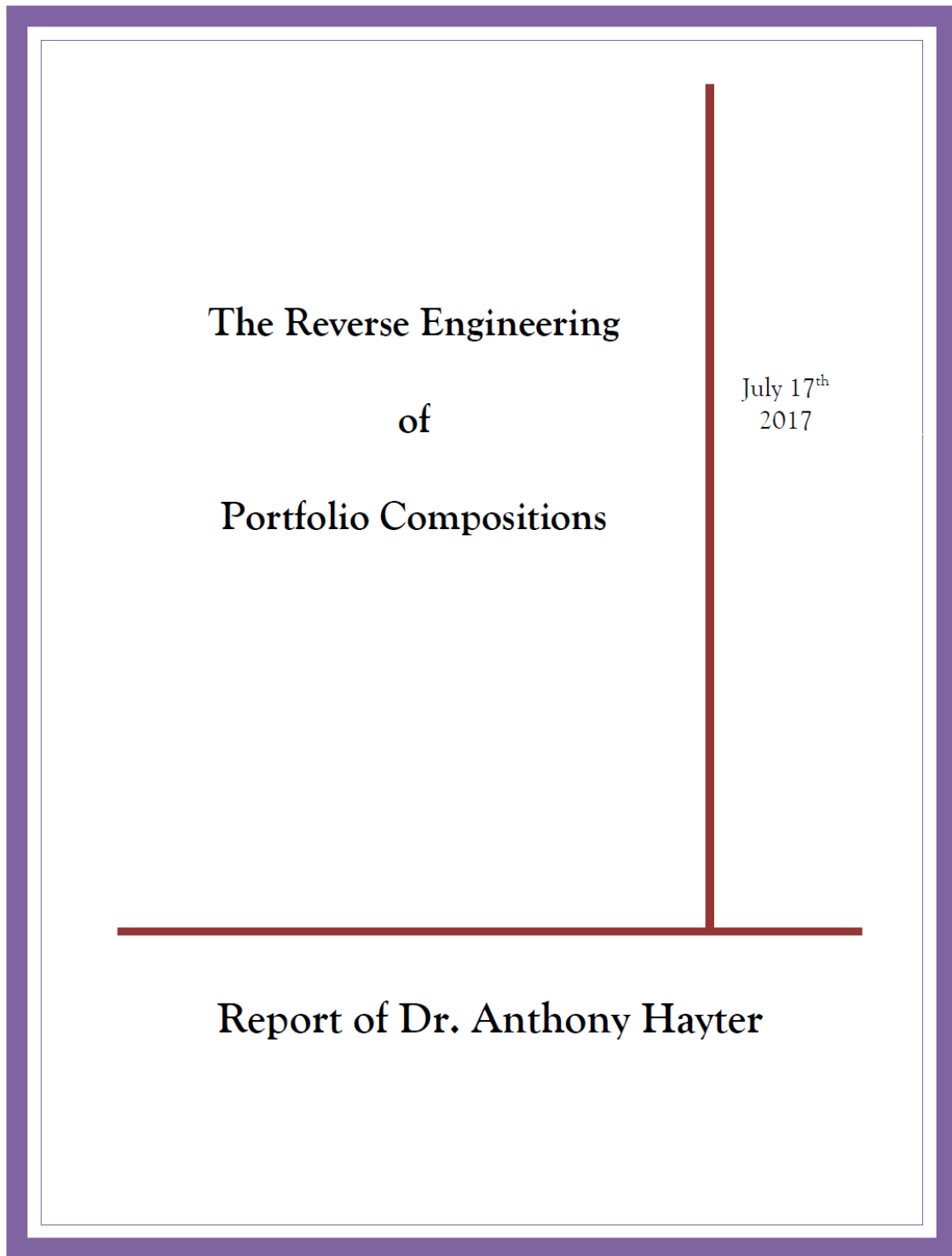
Terence W. Norman  
Founder  
Blue Tractor Group, LLC

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<sup>15</sup> See <https://dealbook.nytimes.com/2013/08/22/computer-bugs-and-squirrels-a-history-of-nasdaqs-woes/>

<sup>16</sup> See <http://money.cnn.com/2015/07/08/investing/nyse-suspends-trading/index.html>

**Appendix One**



### Caveat

The opinions and results set forth in this report are based on an assessment of information currently available to its author. If, when, and to the extent that additional data and information are made available and can be properly evaluated, it is possible that the opinions and results set forth in this report will need to be supplemented and/or modified. The author reserves the right to do so if data and information later made available suggest any such supplementation and/or modification is appropriate.



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## Section I: The Reverse Engineering of Portfolio Compositions.

□ Overview.

In this report I consider the accuracy with which it is possible to reverse engineer a portfolio composition.

Specifically, suppose that a portfolio is known to consist of a subset of stocks from within a known universe of stocks. However, the individual weights of these stocks within the portfolio are unknown, and indeed many of the weights may be zero if those individual stocks are not contained within the portfolio.

The objective of reverse engineering is to estimate the unknown weights of the stocks within the portfolio. In other words, the objective of reverse engineering is to estimate which stocks within the known universe of stocks are actually contained within the portfolio, together with the weights of those stocks within the portfolio.

The information available for the reverse engineering consists of the prices of each of the stocks within the known universe of stocks, together with the price of the portfolio. In this report I have considered prices available at



Dr. Anthony Hayter | Reverse Engineering Portfolio Compositions



15-second time intervals. However, in an attempt to complicate the reverse engineering, the portfolio price is “shielded” through scaling and rounding of its value.

This report contains my results as of this date.



□ **Summary.**

The simulations presented in this report demonstrate that the reverse engineering of a portfolio is achievable with a substantial degree of accuracy. Obviously, the amount of “shielding” of the portfolio price through scaling and rounding of its value directly affects the accuracy of the reverse engineering. In addition, the information available from the 15-second reporting of real stock prices rather than the simulated stock prices considered in this report may affect the accuracy of the reverse engineering. However, for the realistic scenarios considered in this report it is clear that the reverse engineering of a portfolio is achievable with a substantial degree of accuracy.

Moreover, it should be pointed out that the simulation results presented in this report are based upon a simple generic reverse engineering methodology. However, in practice, it would be expected that experts with knowledge of the specific stocks involved, with some prior historical information about the portfolio, and with an understanding of prevailing market conditions, for example, would be able to fine tune a generic methodology such as this in order to improve its performance.



□ Model.

This section contains a description of the model of the portfolio which is used in this report. This model allows an analysis of the effectiveness of reverse engineering for different scenarios.

Consider a known universe of  $k$  stocks. Denote the price of stock  $i$  at time  $t$  as  $X_i(t)$ . The beginning of the time period over which the reverse engineering is conducted is  $t = 0$ .

Suppose that the portfolio consists of  $n_i$  shares in stock  $i$ . The values of the stock holdings  $n_i$  are unknown to the person conducting reverse engineering, and the objective of the reverse engineering is to estimate the values of the  $n_i$ . If the  $i^{\text{th}}$  stock is not included in the portfolio then  $n_i = 0$ .

Denote the portfolio value at time  $t$  as  $PV(t)$ . The portfolio value is related to the stock prices by the equation

$$PV(t) = n_1 X_1(t) + \dots + n_k X_k(t).$$

Specifically, the portfolio value at the initial time point is

$$PV(0) = n_1 X_1(0) + \dots + n_k X_k(0).$$

Suppose that at the start of the time period  $N$  shares are issued for the portfolio, each with a scaled starting price of  $Y(0)$ . Consequently,

$$PV(0) = N Y(0).$$



If the prices of the portfolio shares at subsequent times  $t$  are denoted by  $Y(t)$ , then

$$Y(t) = PV(t) / N .$$

Therefore,

$$Y(t) / Y(0) = w_1 X_1(t) / X_1(0) + \dots + w_k X_k(t) / X_k(0) \quad (1)$$

where the weights  $w_i$  are given by

$$w_i = n_i X_i(0) / (N Y(0))$$

which sum to 1. Notice that a weight  $w_i = 0$  implies that  $n_i = 0$  so that the  $i^{\text{th}}$  stock is not contained within the portfolio.

The weights  $w_i$  represent the proportion of the total value of the portfolio in each of the stocks at the initial time point. The reverse engineering methodology allows the estimation of these weights  $w_i$  which provide estimates of the stock holdings  $n_i$ . In turn, the estimation of the stock holdings  $n_i$  allows the estimation of the proportion of the total value of the portfolio in each of the stocks at any subsequent times  $t$  as the stock prices  $X_i(t)$  change.

In practice only a modified rounded portfolio share value  $Y^*(t)$  of the true portfolio share price  $Y(t)$  at each time point  $t$  is known.



□ **Methodology.**

Equation (1) can be used to estimate the weights  $w_i$  based upon the known stock prices  $X_i(t)$  and the known rounded portfolio share values  $Y^*(t)$  over a series of times  $t$ .

In this report a two-stage generic methodology is adopted. In the first stage a standard multiple linear regression model (without an intercept) is used to obtain initial estimates of the weights  $w_i$  together with p-values for whether the difference between each estimated weight and zero is statistically significant. All estimated weights that are negative are set to zero, together with all estimated weights for which the difference from zero is not statistically significant.

This first stage identifies which stocks are considered to be in the portfolio. The stocks which have estimated weights of zero at the end of the first stage are considered to be excluded from the portfolio. The stocks with strictly positive estimated weights at the end of the first stage are considered to be included in the portfolio.

The second stage of the methodology produces the final estimated weights for the stocks which are considered to be included in the portfolio. Equation (1) is used again, but this time the right hand side only includes the stocks that are considered to be included in the portfolio. The weights  $w_i$  are estimated by minimizing the sum of squares of the differences between the



two sides of the equation at each time point  $t$ , under the constraint that the estimated weights sum to one.

It should be pointed out that the simulation results presented in this report use this generic methodology. However, in practice, it would be expected that experts with knowledge of the specific stocks involved, with some prior historical information about the portfolio, and with an understanding of prevailing market conditions, for example, would be able to fine tune a generic methodology such as this in order to improve its performance.



□ Simulations.

Simulations were conducted in order to assess the accuracy achieved by the reverse engineering for different scenarios.

For each simulation, a set of random stock prices  $X_i(t)$  were obtained over a specified time period. For a set of specified weights  $w_i$  these randomly obtained stock prices were then used to determine the true prices  $Y(t)$  of a portfolio share using equation (1). The reverse engineering methodology was then applied for different roundings and scalings of the true portfolio share prices  $Y(t)$  in order to obtain a set of estimated weights. The accuracy of the reverse engineering methodology was then assessed by comparing these estimated weights to the initially specified weights  $w_i$ .

The random stock prices were obtained by taking the log ratios of the stock prices at successive time points to have independent multivariate normal distributions. Specifically, the stock prices  $X_i(t)$  were modelled as

$$X_i(t+1) = X_i(t) \times \exp(h_i(t))$$

so that

$$h_i(t) = \ln(X_i(t+1) / X_i(t))$$

with  $(h_1(t), \dots, h_k(t))$  being independent observations from a multivariate normal distribution with all standard deviations and all correlations set to specified values  $\sigma$  and  $\rho$  respectively.



In the Appendix it is shown how daily stock volatilities  $\sigma_d$  and correlations  $\rho$  are calculated from a set of Nasdaq-100 stocks. These provide three scenarios for the simulations:

- Worst-case scenario:  $\sigma_d = 0.0137$  and  $\rho = 0.551$ .
- Average scenario:  $\sigma_d = 0.0173$  and  $\rho = 0.278$ .
- Best-case scenario:  $\sigma_d = 0.0237$  and  $\rho = 0.181$ .

The simulations were run with successive time points being 15-seconds apart, which provides 1,560 time points throughout a complete trading day. Consequently, values of  $\sigma = \sigma_d/\sqrt{1,560}$  were used for the standard deviations of the  $h_i(t)$ .

Simulations were conducted for total time periods of 1 day and 5 days of trading. With successive time points being 15-seconds apart, these time periods correspond to a total of 1,560 and 7,800 time points respectively.

In addition, simulations were performed for two different portfolios. The first portfolio consisted of 40 equally weighted stocks selected out of a universe of  $k = 100$  potential stocks. In this case, the weights of the stocks included in the portfolio were  $w_i = 0.025$ . The second portfolio consisted of 20 equally weighted stocks selected out of a universe of  $k = 50$  potential stocks. In this case, the weights of the stocks included in the portfolio were  $w_i = 0.05$ .





As has been discussed, the portfolio share price is “shielded” through scaling and rounding of its value  $Y(t)$ . In the simulations, initial scaled values of  $Y(0) = 20$  and  $Y(0) = 50$  were considered, together with roundings of the portfolio share prices  $Y(t)$  to  $r = 1$ ,  $r = 2$ , and  $r = 3$  decimal places.

Finally, it should be noted that in the first stage of the reverse engineering methodology a significance level of  $\alpha = 0.01$  was used for determining which stocks were excluded from the estimated portfolio. For each set of conditions  $M = 100$  simulations were performed, and the average values of the results over these simulations are presented in Tables 1-4.



□ Results.

The simulation results are presented in four tables:

- Table 1 - Universe of  $k = 100$  potential stocks with 5 days of trading.
- Table 2 - Universe of  $k = 50$  potential stocks with 5 days of trading.
- Table 3 - Universe of  $k = 100$  potential stocks with 1 day of trading.
- Table 4 - Universe of  $k = 50$  potential stocks with 1 day of trading.

The accuracy of the reverse engineering is measured by:

- (1) The number of stocks incorrectly excluded from the estimated portfolio.
- (2) The average absolute difference between the true weight and the estimated weight for the stocks in the portfolio.
- (3) The number of stocks incorrectly included in the estimated portfolio.
- (4) The sum of the estimated weights for stocks incorrectly included in the estimated portfolio.

Notice that the reverse engineering is *more accurate* as each of these four criteria is *smaller*.

Comparisons of Tables 1-4 indicate that the accuracy with which the reverse engineering can be performed *increases* as:

- The universe of potential stocks is *smaller*.



- The time period considered is *longer*.
- The volatility of the stocks *increases*.
- The correlation between the stocks *decreases*.
- The initial scaled price of the portfolio share is *larger*.
- The rounding of the portfolio share price is *less severe*.

As would be expected, the simulations with  $r = 1$  (so that the portfolio share price is rounded to one decimal place) demonstrate that the reverse engineering is not very accurate in these cases. The simulations show that with  $r = 1$  both a substantial number of stocks are incorrectly excluded from the estimated portfolio, and a substantial number of stocks are incorrectly included in the estimated portfolio.

For an initial scaled portfolio share price of  $Y(0) = 20$  there must generally be a change in the portfolio share price of  $0.1/20 = 0.5\%$  for the change to register in the rounded modified portfolio share price  $Y^*(t)$ . Similarly, for an initial scaled portfolio share price of  $Y(0) = 50$  there must generally be a change in the portfolio share price of  $0.1/50 = 0.2\%$  for the change to register in the rounded modified portfolio share price  $Y^*(t)$ . As indicated, it would not be expected for the reverse engineering to be accurate in these cases with such severe rounding, and this is validated by the simulation results.



However, with  $r = 2$  and  $r = 3$  (so that the portfolio share price is rounded to either two or three decimal places) the simulations demonstrate that the reverse engineering can be very accurate. As an example, consider the average scenario for daily volatility and correlations of the stock prices  $X_i(t)$  and the case with a potential universe of  $k = 100$  stocks where the reverse engineering is conducted over 5 days of trading. For an initial scaled portfolio share price of  $Y(0) = 20$  with  $r = 2$  it can be seen from Table 1 that all 40 of the stocks in the portfolio were correctly included in the estimated portfolio. Furthermore, the average error in estimating the weights  $w_i = 0.025$  is only 0.000511, which is  $0.000511/0.025 = 2.0\%$ . As the scaled price rises to  $Y(0) = 50$  with  $r = 2$  the average error falls to 0.000196 which is  $0.000196/0.025 = 0.8\%$ .

In addition, for this case with an initial scaled portfolio share price of  $Y(0) = 20$  with  $r = 2$  it can be seen from Table 1 that out of the 60 stocks that are not included in the portfolio, the average number included in the estimated portfolio is only 0.47 (so that in more than half of the simulations none of these 60 stocks were incorrectly included in the estimated portfolio). Moreover, even if one of these 60 stocks were incorrectly included in the estimated portfolio, the weight within the estimated portfolio is only 0.000575 on average, which is a weight of only 0.0575%.

As the scaled price rises to  $Y(0) = 50$  with  $r = 2$  out of the 60 stocks that are not included in the portfolio, the average number included in the estimated portfolio is only 0.31 (so that in more than two thirds of the



simulations none of these 60 stocks were incorrectly included in the estimated portfolio). In this case, even if one of these 60 stocks were incorrectly included in the estimated portfolio, the weight within the estimated portfolio is only 0.000142 on average, which is a weight of only 0.0142%.

The accuracy of the reverse engineering improves in Table 2 relative to Table 1 where, still with 5 days of trading, the potential universe of stocks is reduced to  $k = 50$ . Now for the average scenario of daily volatility and correlations of the stock prices  $X_i(t)$ , with  $Y(0) = 20$  and  $r = 2$  the average error in estimating the weights  $w_i = 0.05$  is only 0.000368, which is  $0.000368/0.05 = 0.7\%$ , while the weight within the estimated portfolio of stocks excluded from the true portfolio is only 0.000187 on average, which is a weight of only 0.0187%. With  $Y(0) = 50$  and  $r = 2$  the average error in estimating the weights  $w_i = 0.05$  is only 0.000137, which is  $0.000137/0.05 = 0.3\%$ , while the weight within the estimated portfolio of stocks excluded from the true portfolio is only 0.000026 on average, which is a weight of only 0.0026%.

It should be noted that this accuracy of the reverse engineering methodology has been achieved with  $r = 2$  so that the portfolio share price is rounded to two decimal places. For an initial scaled portfolio share price of  $Y(0) = 20$  there must generally be a change in the portfolio share price of  $0.01/20 = 0.05\%$  for the change to register in the rounded modified portfolio share price  $Y^*(t)$ . Similarly, for an initial scaled portfolio share price of  $Y(0) = 50$  there must generally be a change in the portfolio share price of



$0.01/50 = 0.02\%$  for the change to register in the rounded modified portfolio share price  $Y^*(t)$ . Nevertheless, in spite of this the simulations demonstrate the accuracy of the reverse engineering methodology in these cases.

Finally, Tables 3 and 4 correspond to Tables 1 and 2 respectively, but with the reverse engineering conducted over a time period of 1 trading day rather than 5 days. Of course, the simulations demonstrate that the reverse engineering is less accurate over the shorter time period. Nevertheless, even in this shorter time period the reverse engineering can be quite successful.

For example, with  $Y(0) = 20$  and  $r = 2$  say, and with the average scenario for daily volatility and correlations of the stock prices  $X_i(t)$  and the case with a potential universe of  $k = 100$  stocks where the reverse engineering is conducted over only 1 day, it can be seen from Table 3 that the average error in estimating the weights  $w_i = 0.025$  is only 0.003074, which is  $0.003074/0.025 = 12.3\%$ . As the scaled price rises to  $Y(0) = 50$  with  $r = 2$  the average error falls to 0.001016 which is  $0.001016/0.025 = 4.1\%$ . The weight within the estimated portfolio of stocks excluded from the true portfolio is only 0.001959 on average with  $Y(0) = 20$  and  $r = 2$ , which is a weight of only 0.1959%, and is only 0.000778 on average with  $Y(0) = 50$  and  $r = 2$ , which is a weight of only 0.0778%.



Table 1					
Universe of $k = 100$ potential stocks. Portfolio contains 40 stocks with equal weights 0.025.					
Estimation based on 5 days of stock prices.					
Table entries are average values based on $M = 100$ simulations.					
Initial scaled value $Y(0)$ of a portfolio share.	Portfolio share price rounded to $r$ decimal places.	Number of stocks incorrectly excluded from the estimated portfolio.	Average absolute difference between true weight 0.025 and estimated weight for the 40 stocks in the portfolio.	Number of stocks incorrectly included in the estimated portfolio.	Sum of estimated weights for stocks incorrectly included in the estimated portfolio.
Worst-case scenario for daily volatility and correlations: $\sigma_d = 0.0137$ and $\rho = 0.551$ .					
$Y(0) = 20$	$r = 1$	25.27	0.025176	10.57	0.354038
$Y(0) = 20$	$r = 2$	0	0.000776	0.31	0.000565
$Y(0) = 20$	$r = 3$	0	0.000081	0.27	0.000056
$Y(0) = 50$	$r = 1$	9.69	0.014277	5.38	0.094444
$Y(0) = 50$	$r = 2$	0	0.000322	0.29	0.000202
$Y(0) = 50$	$r = 3$	0	0.000033	0.43	0.000034
Average scenario for daily volatility and correlations: $\sigma_d = 0.0173$ and $\rho = 0.278$ .					
$Y(0) = 20$	$r = 1$	20.97	0.022152	12.01	0.303314
$Y(0) = 20$	$r = 2$	0	0.000511	0.47	0.000575
$Y(0) = 20$	$r = 3$	0	0.000051	0.36	0.000042
$Y(0) = 50$	$r = 1$	1.44	0.006201	5.76	0.047818
$Y(0) = 50$	$r = 2$	0	0.000196	0.31	0.000142
$Y(0) = 50$	$r = 3$	0	0.000020	0.21	0.000008
Best-case scenario for daily volatility and correlations: $\sigma_d = 0.0237$ and $\rho = 0.181$ .					
$Y(0) = 20$	$r = 1$	14.94	0.017910	12.21	0.235816
$Y(0) = 20$	$r = 2$	0	0.000340	0.29	0.000238
$Y(0) = 20$	$r = 3$	0	0.000034	0.30	0.000024
$Y(0) = 50$	$r = 1$	0.02	0.002996	4.98	0.022786
$Y(0) = 50$	$r = 2$	0	0.000139	0.22	0.000060
$Y(0) = 50$	$r = 3$	0	0.000014	0.21	0.000007



Table 2					
Universe of $k = 50$ potential stocks. Portfolio contains 20 stocks with equal weights 0.05.					
Estimation based on 5 days of stock prices.					
Table entries are average values based on $M = 100$ simulations.					
Initial scaled value $Y(0)$ of a portfolio share.	Portfolio share price rounded to $r$ decimal places.	Number of stocks incorrectly excluded from the estimated portfolio.	Average absolute difference between true weight 0.05 and estimated weight for the 40 stocks in the portfolio.	Number of stocks incorrectly included in the estimated portfolio.	Sum of estimated weights for stocks incorrectly included in the estimated portfolio.
Worst-case scenario for daily volatility and correlations: $\sigma_d = 0.0137$ and $\rho = 0.551$ .					
$Y(0) = 20$	$r = 1$	6.60	0.033038	6.80	0.241388
$Y(0) = 20$	$r = 2$	0	0.000563	0.13	0.000160
$Y(0) = 20$	$r = 3$	0	0.000055	0.08	0.000011
$Y(0) = 50$	$r = 1$	0	0.004760	2.55	0.019044
$Y(0) = 50$	$r = 2$	0	0.000216	0.17	0.000093
$Y(0) = 50$	$r = 3$	0	0.000022	0.16	0.000009
Average scenario for daily volatility and correlations: $\sigma_d = 0.0173$ and $\rho = 0.278$ .					
$Y(0) = 20$	$r = 1$	2.59	0.022169	6.61	0.152292
$Y(0) = 20$	$r = 2$	0	0.000368	0.19	0.000187
$Y(0) = 20$	$r = 3$	0	0.000035	0.16	0.000013
$Y(0) = 50$	$r = 1$	0	0.003351	3.06	0.015252
$Y(0) = 50$	$r = 2$	0	0.000137	0.11	0.000026
$Y(0) = 50$	$r = 3$	0	0.000014	0.15	0.000005
Best-case scenario for daily volatility and correlations: $\sigma_d = 0.0237$ and $\rho = 0.181$ .					
$Y(0) = 20$	$r = 1$	0.52	0.012969	5.99	0.090213
$Y(0) = 20$	$r = 2$	0	0.000221	0.15	0.000092
$Y(0) = 20$	$r = 3$	0	0.000023	0.06	0.000003
$Y(0) = 50$	$r = 1$	0	0.001989	2.19	0.007002
$Y(0) = 50$	$r = 2$	0	0.000091	0.18	0.000041
$Y(0) = 50$	$r = 3$	0	0.000009	0.16	0.000003





Table 3					
Universe of $k = 100$ potential stocks. Portfolio contains 40 stocks with equal weights 0.025.					
Estimation based on 1 day of stock prices.					
Table entries are average values based on $M = 100$ simulations.					
Initial scaled value $Y(0)$ of a portfolio share.	Portfolio share price rounded to $r$ decimal places.	Number of stocks incorrectly excluded from the estimated portfolio.	Average absolute difference between true weight 0.025 and estimated weight for the 40 stocks in the portfolio.	Number of stocks incorrectly included in the estimated portfolio.	Sum of estimated weights for stocks incorrectly included in the estimated portfolio.
Worst-case scenario for daily volatility and correlations: $\sigma_d = 0.0137$ and $\rho = 0.551$ .					
$Y(0) = 20$	$r = 1$	34.59	0.031714	5.51	0.475218
$Y(0) = 20$	$r = 2$	12.04	0.017951	0.22	0.006805
$Y(0) = 20$	$r = 3$	0	0.000399	0.29	0.000290
$Y(0) = 50$	$r = 1$	33.83	0.034624	2.87	0.318814
$Y(0) = 50$	$r = 2$	0	0.001622	0.33	0.001216
$Y(0) = 50$	$r = 3$	0	0.000158	0.16	0.000056
Average scenario for daily volatility and correlations: $\sigma_d = 0.0173$ and $\rho = 0.278$ .					
$Y(0) = 20$	$r = 1$	32.96	0.031253	5.90	0.419461
$Y(0) = 20$	$r = 2$	0.31	0.003074	0.25	0.001959
$Y(0) = 20$	$r = 3$	0	0.000255	0.34	0.000219
$Y(0) = 50$	$r = 1$	30.21	0.031926	3.93	0.262568
$Y(0) = 50$	$r = 2$	0	0.001016	0.32	0.000778
$Y(0) = 50$	$r = 3$	0	0.000100	0.30	0.000066
Best-case scenario for daily volatility and correlations: $\sigma_d = 0.0237$ and $\rho = 0.181$ .					
$Y(0) = 20$	$r = 1$	31.31	0.029802	7.11	0.405604
$Y(0) = 20$	$r = 2$	0	0.001748	0.30	0.001446
$Y(0) = 20$	$r = 3$	0	0.000173	0.28	0.000106
$Y(0) = 50$	$r = 1$	26.90	0.030162	3.29	0.179467
$Y(0) = 50$	$r = 2$	0	0.000663	0.22	0.000393
$Y(0) = 50$	$r = 3$	0	0.000069	0.30	0.000049



Table 4					
Universe of $k = 50$ potential stocks. Portfolio contains 20 stocks with equal weights 0.05.					
Estimation based on 1 day of stock prices.					
Table entries are average values based on $M = 100$ simulations.					
Initial scaled value $Y(0)$ of a portfolio share.	Portfolio share price rounded to $r$ decimal places.	Number of stocks incorrectly excluded from the estimated portfolio.	Average absolute difference between true weight 0.05 and estimated weight for the 40 stocks in the portfolio.	Number of stocks incorrectly included in the estimated portfolio.	Sum of estimated weights for stocks incorrectly included in the estimated portfolio.
Worst-case scenario for daily volatility and correlations: $\sigma_d = 0.0137$ and $\rho = 0.551$ .					
$Y(0) = 20$	$r = 1$	14.73	0.056376	4.15	0.392685
$Y(0) = 20$	$r = 2$	0	0.002669	0.11	0.000799
$Y(0) = 20$	$r = 3$	0	0.000271	0.14	0.000104
$Y(0) = 50$	$r = 1$	11.30	0.052647	2.08	0.152444
$Y(0) = 50$	$r = 2$	0	0.001087	0.17	0.000389
$Y(0) = 50$	$r = 3$	0	0.000105	0.10	0.000027
Average scenario for daily volatility and correlations: $\sigma_d = 0.0173$ and $\rho = 0.278$ .					
$Y(0) = 20$	$r = 1$	12.93	0.051115	4.78	0.350672
$Y(0) = 20$	$r = 2$	0	0.001692	0.15	0.000525
$Y(0) = 20$	$r = 3$	0	0.000177	0.11	0.000052
$Y(0) = 50$	$r = 1$	5.19	0.030163	2.39	0.093539
$Y(0) = 50$	$r = 2$	0	0.000677	0.08	0.000121
$Y(0) = 50$	$r = 3$	0	0.000069	0.16	0.000022
Best-case scenario for daily volatility and correlations: $\sigma_d = 0.0237$ and $\rho = 0.181$ .					
$Y(0) = 20$	$r = 1$	10.58	0.044994	4.69	0.274717
$Y(0) = 20$	$r = 2$	0	0.001129	0.17	0.000456
$Y(0) = 20$	$r = 3$	0	0.000119	0.16	0.000050
$Y(0) = 50$	$r = 1$	1.27	0.013673	2.23	0.048700
$Y(0) = 50$	$r = 2$	0	0.000457	0.17	0.000182
$Y(0) = 50$	$r = 3$	0	0.000048	0.17	0.000018



□ Appendix – Calculation of Historical Stock Volatilities and Correlations.

This appendix contains an analysis of the volatility and correlations of 10 stocks from the Nasdaq-100 index. When the Nasdaq-100 stocks are listed alphabetically, the 1<sup>st</sup>, 11<sup>th</sup>, 21<sup>st</sup>, ... , 91<sup>st</sup>, stocks were selected for the analysis.

The closing stock prices were considered for each trading day within the past 5 years, and the log price ratios from day to day were calculated. Table 5 contains the standard deviations  $\sigma_a$  of these daily log price ratios for each of the 10 stocks, and Table 6 contains the correlations  $\rho$  of these daily log price ratios between the 10 stocks.

The standard deviations  $\sigma_a$  have an average of 0.0173 with a minimum of 0.0137 and a maximum of 0.0237. The correlations  $\rho$  have an average of 0.278 with a minimum of 0.181 and a maximum of 0.551.

It is known both intuitively and from the simulation results that the accuracy of the reverse engineering *increases* as the volatility of the stock prices *increases*, and as the correlations between the stock prices *decrease*. Consequently, in terms of the ease with which the reverse engineering can be performed, a worst-case scenario, an average scenario, and a best-case scenario can be identified as:



- Worst-case scenario:  $\sigma_d = 0.0137$  and  $\rho = 0.551$ .
- Average scenario:  $\sigma_d = 0.0173$  and  $\rho = 0.278$ .
- Best-case scenario:  $\sigma_d = 0.0237$  and  $\rho = 0.181$ .



Table 5: Standard deviations of the daily log price ratios.


Stock	Standard Deviation
AAL	0.0237
AMZN	0.0184
CHTR	0.0166
DISCK	0.0161
FOX	0.0137
INTC	0.0138
LBTYA	0.0170
MYL	0.0204
ROST	0.0140
VIAB	0.0191



Table 6: Correlations of the daily log price ratios.

Correlations									
	AAL	AMZN	CHTR	DISCK	FOX	INTC	LBTYA	MYL	ROST
AMZN	0.197								
CHTR	0.217	0.269							
DISCK	0.233	0.229	0.295						
FOX	0.275	0.316	0.307	0.503					
INTC	0.282	0.266	0.244	0.320	0.284				
LBTYA	0.269	0.301	0.352	0.375	0.440	0.269			
MYL	0.252	0.181	0.232	0.217	0.260	0.205	0.277		
ROST	0.219	0.249	0.198	0.225	0.315	0.229	0.223	0.188	
VIAB	0.213	0.228	0.235	0.495	0.551	0.301	0.361	0.211	0.183






## Section II: Data and Information Considered.

The following data and information have been considered for the preparation of this report.

- (1) “Precidian’s Proposed ETF and the Possibility of Reverse Engineering”, July 2015, Dr. R.A. Cooper.
- (2) “Additional Research on the Ability to Reverse Engineer the Proposed Precidian ETF”, August 2015, Dr. R.A. Cooper.
- (3) Stock price data.






### Section III: The Qualifications of Dr. Anthony Hayter.

I am currently a Full Professor in the Department of Business Information and Analytics at the University of Denver. Between 2006 and 2010 I was the Chair of the Department of Statistics and Operations Technology at the University of Denver, holding the rank of Full Professor.

I have an M.A. in mathematics from Cambridge University, England, scoring a first class in each of my three years there. I obtained my Ph.D. in Statistics from Cornell University at the age of 23. I have spent almost my entire career in an academic environment, and for about thirty years I have held university positions with responsibilities for teaching and researching statistics, probability, and data analysis.

I have established a collaborative research program which has so far resulted in over 90 refereed journal publications, and I have delivered many conference presentations. I have taught a wide range of courses related to statistics, probability, and data analysis at both undergraduate and graduate levels, and I have delivered several keynote addresses at meetings and conferences.



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I am the author of the textbook “*Probability and Statistics for Engineers and Scientists*,” the 4th edition of which was published in 2012, and which has been adopted at over sixty universities around the world. I have personally advised eight doctoral students. In addition, I have served as an associate editor of three research journals, and I have presented 88 invited research seminars worldwide.

I have global interests and I have spent considerable time in Japan where I have taught statistics, probability, and data analysis in some Japanese MBA programs. I have received various grants to visit Japanese research institutions and I have also been funded as a visiting researcher in England, Thailand, Singapore, and Hong Kong.

I was awarded a Fulbright Foreign Scholarship Award in 2011-2012 and a Fulbright Specialist Grant in 2014 to assist the government, universities, and businesses in Thailand with surveys, data analysis, curriculum development and research projects.

My full resume is available at [HayterStatistics.com](http://HayterStatistics.com).



Signature Page

I hereby certify that the above report was written by me.

Signed :



Dr. Anthony Hayter

July 17<sup>th</sup>, 2017



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