Trading QQQ ETF 5min Bars Using the nth Order Fixed Memory Polynomial Velocity Algorithm
Walk Forward in-sample 20 Trading weekdays and out-of-sample 1 Trading weekday.
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In previous working papers at https://meyersanalytics.com/papers we showed how the application of a price curve generated by the **Nth Order Fixed Memory Polynomial Velocity** could be used to develop a strategy to buy and sell futures and stocks intraday. The reasoning behind this type of strategy was to only trade when the price trend velocity was above a certain threshold. Many times, prices meander around without any notable trend, and this is considered noise. During these times we do not wish to trade because of the cost of whipsaw losses that would occur from this type of price action. When a price trend finally starts, the velocity of that price trend moves above a minimum threshold noise value. Thus, the velocity strategy would only issue a trade when certain velocity thresholds above "noise" levels are crossed.

The velocity strategy that we will use here to trade the Invesco QQQ Trust Series ETF (**QQQ**) is called the nth Order Polynomial Velocity Strategy. The nth Order Adaptive Polynomial Velocity Strategy has several unknown inputs that we must determine before we can use this strategy to trade. These unknown inputs are the polynomial order or degree, the optimum number of lookback prices we need to determine the coefficients of the polynomial and finally the velocity thresholds. Here we will use Walk Forward Optimization and out-of-sample testing to determine the "best" polynomial inputs as well as how these inputs change over time. We will use the nth Order Fixed Memory Polynomial Velocity Strategy to trade the QQQ ETF on an intraday basis using 5-min bar price data from 01/02/2022 to 8/4/2023.

The n^{th} Order Fixed Memory Velocity Strategy Defined
The least squares forecast n^{th} order fixed memory polynomial velocity is constructed by solving for the coefficients $\beta_0, \beta_1, \beta_2, \beta_3 \ldots \beta_n$ for the discrete orthogonal Legendre polynomials each day using the last **N bars** of closing prices and the equation for β_j shown in the **"Math"** appendix at the end of this working paper. Then n^{th} Order Fixed Memory Polynomial **Velocity(T+1)** is constructed from the equation shown in the "Math" appendix.

Due to polynomial mathematics, the Velocity of the 2^{nd}, 3^{rd} and 4^{th} order degree polynomial curve changes faster than it's corresponding first order degree polynomial velocity. Whether higher order polynomial velocities are an advantage or not, will be determined by the computer when we use a walk forward optimization technique described below.

At each bar we calculate the nth order degree (1^{st} through 4^{th}) fixed memory polynomial velocity from the formulas in the "Math" appendix. As will be shown below, walk forward optimization will determine the **degree** for the nth order polynomial velocity, the number of lookback prices, **N**, needed to compute the polynomial coefficients and the threshold amounts **vup** and **vdn**. When the nth order degree velocity is greater than the threshold amount ***vup*** we will go long. When the velocity is less than the threshold amount ***-vdn*** we will go short.

Buy Rule:
IF Velocity is greater or equal than the threshold amount ***vup and Velocity[1] is less than vup*** then buy at the market.

Sell Rule:
IF Velocity is less than or equal than the threshold amount ***-vdn and Velocity[1] is greater than -vdn*** then sell at the market.

Where Velocity[1] is the velocity on the previous bar.

Intraday Bars Exit Rule:

Close the position at 1555 EST (No trades will be carried overnight).

Testing The Polynomial Velocity Strategy Using Walk Forward Optimization

There will be four strategy parameters to determine:

1. **degree**, degree=1 for straight line velocity, degree=2 for 2^{nd} order velocity, etc.
2. ***N***, is the number of lookback bars of prices to calculate the **velocity.**
3. ***vup***, the threshold amount that velocity must be greater than to issue a buy signal.
4. ***vdn***, the threshold amount that velocity must be less than to issue a sell signal.

As mentioned, to test this Strategy we will use five-minute bar prices of the QQQ ETF traded on the NYSE and known by the symbol QQQ for the 381 trading days from January 2,2022 to August 4 2023.

We will test the FixmVn strategy with the above QQQ ETF 5 min bars on a ***walk forward basis***, where the in-sample (***IS***) will be 20 trading weekdays and the out-of-sample (***OOS***) will be the next trading weekday following as will be described below.

What Is a Walk Forward Optimization with In-Sample Section and Out-Of-Sample Sections?

Whenever we do a TradeStation or Multicharts (TS/MC) optimization on many different strategy inputs, TS/MC generates a report of performance metrics (total net profits, number of losing trades, etc.) vs these different strategy inputs. If the report is sorted on say the total net profits(***tnp***) performance metric column, then the highest ***tnp*** would correspond to a certain set of inputs. This is called an ***in-sample (IS) section***. If we choose a set of strategy inputs from this report based upon some performance metric, we have no idea whether these strategy inputs will produce the same results on future price data or data they have not been tested on. Price data that is not in the in-sample section is defined as ***out-of-sample data***. Since the performance metrics generated in the in-sample section are mostly due to “curve fitting” or "data mining" it is important to see how the strategy inputs chosen from the in-sample section perform on out-of-sample data.

What do we mean by ***“curve fitting” or data mining?*** As a simple example, suppose you were taking a subway to work. In the subway car you are in, suppose you counted the number of blond women in that car and suppose the percent of blond women vs all other women hair colors was 80%. Being that you cannot observe what is in the other subway cars, you would assume that all the other subway cars and perhaps all women had the same percentage of blond hair. This observation was due to chance. That is an example of curve fitting. The same goes for combinatorial searches. You are observing results from a finite sample of data without knowing the data outside the sample you examined.

Walk forward analysis attempts to minimize the curve fitting of price noise by using the law of averages from the Central Limit Theorem on the out-of-sample performance. In walk forward analysis the data is broken up into many in-sample and out-of-sample sections. Usually for any strategy, one has some performance metric selection procedure, which we will call a ***filter,*** used to select the strategy input parameters from the optimization run. For instance, a ***filter*** example might be all cases that have a profit factor (PF) greater than 1 and less than 3. For the number of cases left, we might select the cases that had the best percent profit. This procedure would leave you with one case in the in-sample section output and its associated strategy input parameters. Now suppose we ran our optimization on each of our many in-sample sections and applied our ***filter*** to each in-sample section output. We would then use the strategy input parameters found by the ***filter*** in each in-sample section on the out-of-sample section immediately following that in-sample section. The input parameters found in each in-sample section and applied to each out-of-sample section would produce independent net profits or losses for each of the out-of-sample sections. Using this method, we now have "x" number of independent out-of-sample section profit and losses from our ***filter***. If we take the average of these out-of-sample section net profits and losses, then we will have an estimate of how our strategy will perform on average. Due to the Central Limit Theorem, as your sample size increases, the spurious noise results in the out-of-sample section performance tend to average out to zero in the limit, leaving us with what to expect from our strategy and filter. ***Mathematical note: This assumption assumes that the out-of-sample returns are from probability distributions that have a finite variance*****.**

Why use the walk forward technique? Why not just perform an optimization on the whole price series and choose the input parameters that give the best total net profits or profit factor or some other performance metric? Surely the price noise cancels itself out with such a large number of in-sample prices and trades. Unfortunately, nothing could be farther from the truth! Optimization is a misnomer and should really be called combinatorial search. As stated above, whenever we run a combinatorial search over many different combinations of input parameters on noisy data on a fixed number of prices, ***no matter how many***, the best performance parameters found are guaranteed to be due to ***"curve fitting"*** the noise and signal. The price series that we trade consists of random spurious price movements, which we call noise, and repeatable price patterns (*if they exist*). When we run, for example, 5000 different inputs parameter combinations, the best performance parameters will be from those strategy input variables that are able to produce profits from the price pattern ***and*** the random spurious movements While the price patterns will repeat, the same spurious price movements will not. If the spurious price movements that were captured by a certain set of input parameters were a large part of the total net profits, as they are in real intraday price series, then choosing these input parameters will produce losses when traded on future data. These losses occur because the spurious price movements will not be repeated in the same way. This is why strategy optimization or combinatorial searches, also called back testing, with no out-of-sample testing cause loses when traded in real time from something that looked great in the in-sample section.

To gain confidence that our input parameter selection method or filter, using the optimization output of the in-sample data, will produce profits, we must test the input parameters we found in the in-sample section on out-of-sample data. In addition, we must perform the in-sample/out-of-sample analysis many times. Why not just do the out-of-sample analysis once or just 10 times? Well just as in Poker or any card game, where there is considerable variation in luck from hand to hand, walk forward out-of-sample analysis give considerable variation in out-of-sample profit "luck". That is, by pure chance we may have chosen some input parameter set that did well in the in-sample section data ***and*** the out-of-sample section data. In order to minimize this type of "luck", statistically, we must repeat the walk forward out-of-sample (**OOS**) analysis over many (>50) in-sample/out-of-sample sections and take an average over all out-of-sample sections. This average gives us an expected out-of-sample return and a standard deviation of out-of-sample returns which allows us to statistically estimate the expected equity and its range for N out-of-sample periods in the future.

Finding The FixmVn Strategy Parameters Using Walk Forward Optimization
There are four strategy parameters to find*, pw, N, vup, vdn.*

For the test data we will run the TS or MC optimization engine on **QQQ** 5 min price bars from 01/02/2022 to 8/4/2023 with the following optimization ranges for the FixmVn strategy inputs. This will create **394, 20 weekday in-sample periods each followed by a 1 day out-of-sample period** (See Figure 1 for the in-sample/out-of-sample periods). The days are weekdays only. Weekdays where the OOS falls on an exchange holiday or partial days are eliminated. Holidays that fall on a weekday create a 19-day ***IS***. All other ***IS*** periods consist of 20 trading weekdays. The optimization ranges are:

1. **pw=degree from 1 to 3**
2. **N from 5 to 20 in steps of 1.**
3. **vup from 0.25 to 3.5 steps of 0.25**
4. **vdn from 0.25 to 3.5 in steps of 0.25**
5. **Mult = 13.8, iNorm=1 (See Appendix 3, the Normalization Multiplier)**

The above pw, n, vup, vdn will produce 9408 different input combinations or cases of the strategy input parameters for each of the 381 in-sample/out-of-sample files for the 19 months of 5 min bar QQQ data. Note the first 20-day trading in-sample period starts at 02/01/2022.

Finding the Best Set of Strategy Inputs to use with an in-sample Metric Filter.

The PWFO generates a number of performance metrics in the in-sample section. (Please see **http://meyersanalytics.com/Walk-Forward-Optimization.html** for a listing of these performance metrics).The question we are attempting to answer statistically, is which performance metric or combination of performance metrics (which we will call a ***filter***) applied to a given set of strategy inputs in the ***in-sample*** section will produce statistically valid profits in the sum of all out-of-sample sections. In other words, we wish to find the best set of strategy inputs ***with a metric filter applied*** in each **in-sample** section that gives the "best" total out-of-sample results over all out-of-sample sections. This means if we applied our ***metric filter*** to the strategy inputs chosen in the in-sample section, we would ***only trade using those set of strategy inputs*** in the next out-of-sample section if the in-sample ***metric filter*** satisfied our criteria. ***Else no trades would be made*** in the next out-of-sample section.

The Walk Forward Strategy – Strategy Inputs with Metric Filters Explorer.

We wish to find ***one*** set of strategy inputs that we can trade in every out-of-sample section, but we will only trade that set of strategy inputs in the out-of-sample section if and only if they satisfy our in-sample ***metric-filter***. Else we will not trade the next out-of-sample section. In this paper the in-sample section is 20 trading days, and the out-of-sample section is the next trading day. After running the PWFO on the in-sample data, we examine the in-sample metric filter that we chose. If the strategy inputs we selected satisfy the in-sample metric filter requirements then we use those strategy inputs to trade the next day. If the strategy inputs do not satisfy the in-sample metric filter, we do not trade the next day.

Let us define the in-sample ***metric-filters*** we will examine here: in-sample Profit Factor (**PF≤ x**) and/or Losers in a row (**lr ≤ y)**,and/or equity curve straight line correlation coefficient t(**r^2(R2) ≤z)**. That is **PF ≤ x and/or lr≤ y and/or R2 ≤ z.**

What we are going to do here is look at every combination in the in-sample section of each **strategy input** with **PF ≤ x and/or lr<y and/or R2 ≤ z**. This will produce seven **strategy input|metric-filter** combinations:

1. **strategy input|PF ≤ x, lr≤y, R2 ≤ z|**
2. **strategy input|PF ≤ x, lr ≤ y|**
3. **strategy input|PF ≤ x, R2 ≤ z|**
4. **strategy input|PF ≤ x |**
5. **strategy input|LR ≤ y, R2 ≤ z|**
6. **strategy input|lr ≤ x|**
7. **strategy input|R2 ≤ z|**
8. **strategy input – we also examine inputs with no filter**

If the **strategy input|metric-filter** satisfies **the metric-filte**r condition in the in-sample section, then we will use those strategy inputs to trade in the out-of-sample section. If not, then there will be no trades in the out-of-sample section.

We will look at all **metric-filter** combinations of **PF≤2 to 5 step 1, LR≤3,5 step 2 and R2≤60 to 80 step 10.** We will also look at the strategy input with no metric-filter. With 9408 different strategy input combinations this will give us 564479 **strategy input|metric-filter** combinations. Each one of these 564479-strategy **input|metric-filter** combinations will be applied to each in-sample section and their out-of-sample performance will be tabulated for all 381 PWFO files.

Below is a snippet of the output from a run of all 564479 combinations sorted by **tONP = total OOS net profit for each strategy input|metric-filter** combination. ***The column definitions are defined in Figure 3 below***. This example shows a partial output file from the WFINP program run on the PWFO files generated with the FixmVn that was run on 100 shares of QQQ ETF 5-minute bars 381 days from 01/02/2022 to 8/4/2023. The in-sample (IS) period is 20 trading weekdays, and the out-of-sample (OOS) period is 1 trading weekday. This strategy traded between 9am to 1555pm Exchange Time (EST).

From this run, we chose the filter on row 4 of the Figure below. That is,

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2|11|1.5|3|0|1555|13.8| r2<80. This is constructed as follows. For the strategy inputs **2|11|1.5|3|0|1555|13.8|** only those in-sample sections that have **r2≤80** are used to trade in the following out-of-sample sections. If the in-sample r2>80, then the out-of-sample section following the in-sample section ***is not*** traded.

<table>
<tr><th></th><th>A</th><th>B</th><th>C</th><th>D</th><th>E</th><th>F</th><th>G</th><th>H</th><th>I</th><th>J</th><th>K</th><th>L</th><th>M</th><th>N</th><th>O</th><th>P</th><th>Q</th><th>R</th><th>S</th><th>T</th><th>U</th><th>V</th><th>W</th><th>X</th><th>Y</th><th>Z</th></tr>
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<tr><td>3</td><td>1|6|1|1.25|0|1555|13.8|pf<2|r2<80</td><td>23221</td><td>20281</td><td>78</td><td>31.6</td><td>2.5</td><td>298</td><td>384</td><td>0.05</td><td>3.1</td><td>3.5</td><td>1.7</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-3565</td><td>8</td><td>5</td><td>18</td><td>88</td><td>92</td><td>94</td><td>131</td><td>232</td><td>3.87E-05</td></tr>
<tr><td>4</td><td>1|7|1|1.5|0|1555|13.8|pf<2|r2<80</td><td>22413</td><td>20197</td><td>80</td><td>40.5</td><td>2</td><td>279</td><td>367</td><td>0.057</td><td>3.32</td><td>3.65</td><td>1.63</td><td>47</td><td>57</td><td>-712</td><td>-949</td><td>-2540</td><td>8</td><td>4</td><td>21</td><td>87</td><td>90</td><td>114</td><td>120</td><td>209</td><td>1.29E-05</td></tr>
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<tr><td>6</td><td>1|6|1|1.25|0|1555|13.8|pf<2|</td><td>23094</td><td>19962</td><td>74</td><td>29.5</td><td>2.5</td><td>313</td><td>388</td><td>0.003</td><td>3.17</td><td>3.36</td><td>1.69</td><td>44</td><td>57</td><td>-583</td><td>-1062</td><td>-3565</td><td>9</td><td>5</td><td>18</td><td>89</td><td>93</td><td>94</td><td>142</td><td>209</td><td>1.08E-04</td></tr>
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<tr><td>9</td><td>2|11|1.5|3|0|1555|13.8|r2<80</td><td>20932</td><td>19624</td><td>89</td><td>64</td><td>1.4</td><td>236</td><td>403</td><td>-0.063</td><td>3.5</td><td>3.38</td><td>1.4</td><td>53</td><td>58</td><td>-1095</td><td>-1128</td><td>-1959</td><td>7</td><td>5</td><td>28</td><td>92</td><td>89</td><td>44</td><td>140</td><td>445</td><td>6.33E-07</td></tr>
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Bootstrap Probability of Filter Results.

Using modern "Bootstrap" techniques, we can calculate the probability of obtaining our filter's total out-of-sample ***net*** profits by chance. Here is how the bootstrap technique is applied. Suppose as an example, we have 500 files of in-sample/out-of-sample data.   A mirror random filter is created. Instead of picking an out-of-sample net profit (OSNP) from a filter row as before, the mirror filter picks a ***random*** row's OSNP in each of the 500 files. We repeat this random picking in each of the 500 files 5000 times. Each of the 5000 mirror filters will choose a random row's OSNP of their own in each of the 500 files. At the end, each of the 5000 mirror filters will have 500 ***random*** OSNP's picked from the rows of the 500 files. The sum of the 500 random OSNP picks for each mirror filter will generate a random total out-of-sample net profit (toNP) or final random equity. The average and standard deviation of the 5000-mirror filter's different random toNPs will allow us to calculate the chance probability of our above chosen filter's toNP. Thus, given the mirror filter's bootstrap random toNP average and standard deviation, we can calculate the probability of obtaining our chosen filter's toNP by pure chance alone. Figure 3 lists the 5000-mirror filter's bootstrap average for our 381 out-of-sample files of **$1.2** with a bootstrap standard deviation of **$16.9**. (Side Note. The average is the average per out-of-sample period. So, the average for the random selection would be the random toNP/381 and the average for the filter would be the filter toNP/# of OOS periods traded or 19624/236=83.1).   The probability of obtaining our filters average daily net profit **of 83.1** is **6.33 x10^{-7}** which is **4.85** standard deviations from the bootstrap average. For our filter, in row 4 above, the expected number of cases that we could obtain by pure chance that would match or exceed **$83.1** is [1-(1-**6.33 x10^{-7}**)^{564479}]**~ 564479*6.33 x10^{-7}** = **.357** where **564479** is the total number of different filters we looked at in this run. This number is less than one, so the probability is small that our result was due to pure chance.

Results

Figure 1 presents a graph of the equity curve generated by using the filter on the 381 days from 2/1/2022 to 8/4/2023. The equity curves are plotted from Equity and Net Equity columns in Table 1. Plotted on the equity curves is the 2nd Order Polynomial curve. The blue line is the equity curve without commissions and the red dots on the blue line are new highs in equity. The brown line is the equity curve with commissions and the green dots are the new highs in net equity. The grey line is the QQQ Daily Closing prices superimposed on the Equity Chart.

Figure 2 presents a plot of the FixmVn Strategy buy/sells and the FixmVn Indicator on the QQQ 5min bars for 6/23/2021 - 8/4/2023.

Table 1 below presents a table of the 381 in-sample and out-of-sample windows, the **Filter** selected in-sample strategy inputs and the daily out-of-sample profit/loss results using the filter described above.

Discussion of Strategy Performance

In Figure 3, Row 9 of the spreadsheet filter output are some statistics that are of interest for our filter. An interesting statistic is **Blw**. **Blw** is the maximum number of days the OSNP equity curve failed to make a new high. **Blw** is **44** days for this filter. This means that 44 trading days was the longest time that the equity for this strategy failed to make a new equity high. **%Wtr** is the percentage of all OOS trades that were wins or positive. For this filter, the **%Wtr=53%**. **%P** is the % winning oos days, **%P=58%**. Both of these are a little lower than I like but the average oos winning trade to the average oos losing trade ratio(**oW|oL**) was **1.4**. **wpr=7** is the maximum number of consecutive winning oos periods(days) in a row and **lpr=5** is the maximum number of consecutive losing oos periods(days) in a row. The Largest losing trade in the whole period was ($1095) and the largest losing day was ($1128). The Maximum drawdown in this period was ($1959) which occurred from 10/25/22 to 11/21/22. Another drawdown of ($1928) occurred between 3/28/22 to 4/18/22.

In Figure 1, which presents a graph of the equity curve using the filter on the 381 trading days of out-of-sample data, notice how the equity curve follows the 2nd order polynomial trend line with an R^2 of 0.969. The R^2 only dropped to 0.964 for the net equity curve.

Using this filter, the strategy was able to generate $19624net equity after commissions of $0 (many brokers today, 8/1/21, don't charge commissions) and slippage of $4 trading 100 QQQ ETF shares for 381 days. This period of time from 2/2/2 to 8/4/23 was a volatile down then up market. Yet the FixmVn strategy was able to adapt quite well.

In observing Table 1 we can see that this strategy and filter made trades from a low of no trades/day to a high of 3 trades/day with an average of 1.4 trades/day on the days it traded. For the no trade days, the strategy **input|filte**r in the in-sample section didn't satisfy the metric filter and no trades were made the next trading day. The **input|filter** traded 236 days out of the 381 days or about 62% of the time.

References

1. Efron, B., Tibshirani, R.J., (1993), "An Introduction to the Bootstrap", New York, Chapman & Hall/CRC.
2. Morrison, Norman "Introduction to Sequential Smoothing and Prediction", McGraw-Hill Book Company, New York, 1969.

Figure 1 Graph of FixmVn Strategy Equity Applying the Walk Forward Filter Each Day on the in-sample section on QQQ 5min Bar Prices 2/1/2022 to 8/4/2023

Note: The blue line is the equity curve without commissions and the red dots on the blue line are new highs in equity.

The brown line is the equity curve with commissions and the green dots are the new highs in net equity.

The grey line is the QQQ Daily Closing prices superimposed on the Equity Chart.

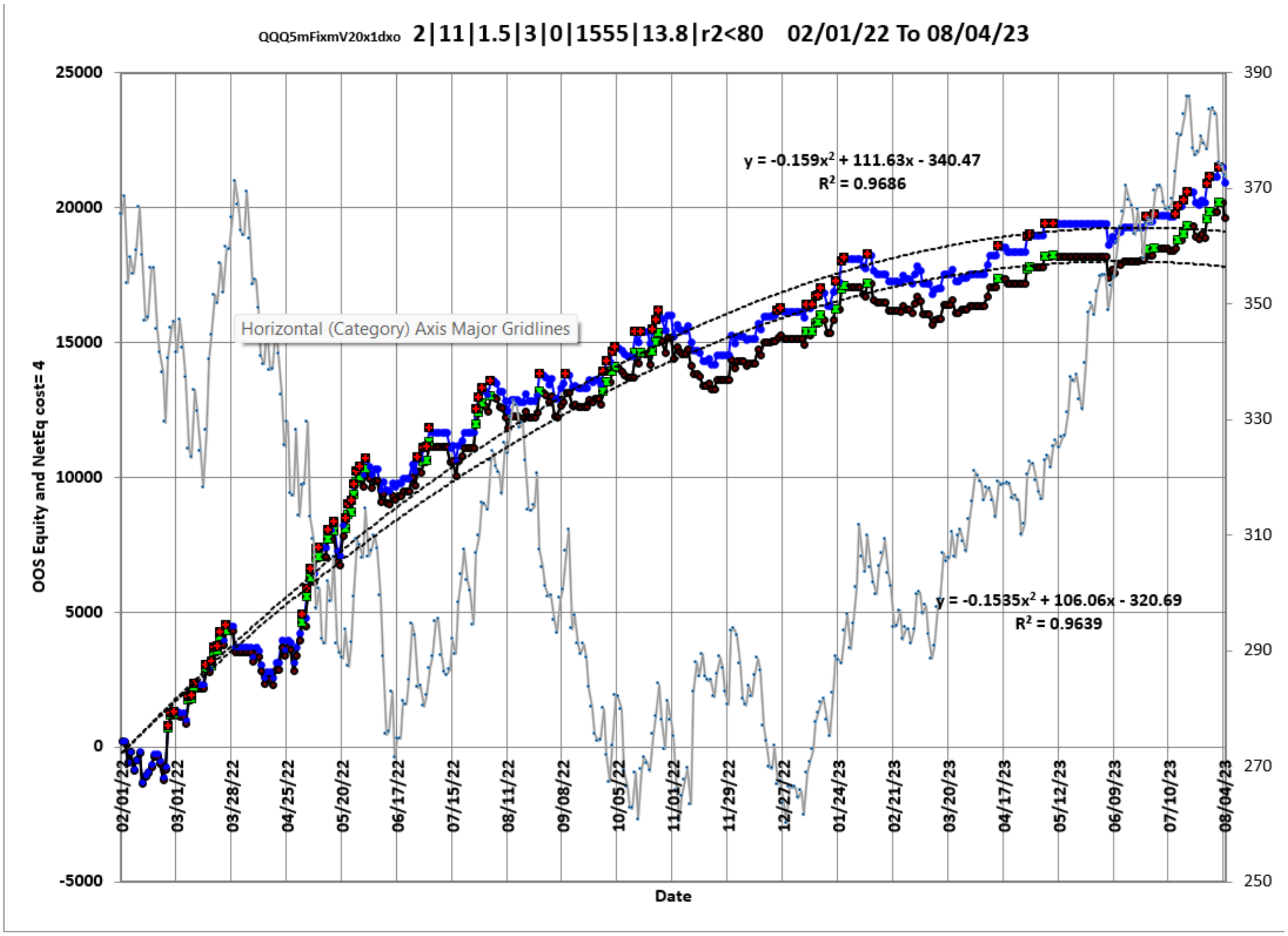

Figure 2 Walk Forward Out-Of-Sample Performance Summary for nth Order Fixed Memory Polynomial Velocity Strategy QQQ 5-minute bar chart from 7/27/23 to 8/4/2023

Figure 3 Partial output of the Walk Forward Strategy Inputs with Metric Filters (WFINP) QQQ ETF 5 min bars Using The FixmVn Strategy

The WFINP Filter Output Columns are defined as follows: OOS=out-of-sample

<table>
<tr><th></th><th>A</th><th>B</th><th>C</th><th>D</th><th>E</th><th>F</th><th>G</th><th>H</th><th>I</th><th>J</th><th>K</th><th>L</th><th>M</th><th>N</th><th>O</th><th>P</th><th>Q</th><th>R</th><th>S</th><th>T</th><th>U</th><th>V</th><th>W</th><th>X</th><th>Y</th><th>Z</th></tr>
<tr><td>1</td><td>QQQ5mFixmV20x1dxo</td><td>s02/01/22</td><td>e08/04/23</td><td>#381</td><td>AnyTnp</td><td></td><td></td><td></td><td></td><td></td><td>lSnt2</td><td></td><td></td><td>a1.2</td><td>s16.9</td><td>f564479</td><td></td><td></td><td></td><td></td><td>c=$4</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>2</td><td>pw|N|vup|vdn|xop|xt|mult|<PF<LR<R2</td><td>toGP</td><td>tONP</td><td>aoGP</td><td>aoTr</td><td>ao#T</td><td>#</td><td>std</td><td>skew</td><td>kur</td><td>t</td><td>oW|oL</td><td>%Wtr</td><td>%P</td><td>LLtr</td><td>LLp</td><td>eqDD</td><td>wpr</td><td>lpr</td><td>V20</td><td>KTau</td><td>eqR2</td><td>Blw</td><td>BE</td><td>tkr|bl</td><td>Prob</td></tr>
<tr><td>3</td><td>1|6|1|1.25|0|1555|13.8|pf<2|r2<80</td><td>23221</td><td>20281</td><td>78</td><td>31.6</td><td>2.5</td><td>298</td><td>384</td><td>0.05</td><td>3.1</td><td>3.5</td><td>1.7</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-3565</td><td>8</td><td>5</td><td>18</td><td>88</td><td>92</td><td>94</td><td>131</td><td>232</td><td>3.87E-05</td></tr>
<tr><td>4</td><td>1|7|1|1.5|0|1555|13.8|pf<2|r2<80</td><td>22413</td><td>20197</td><td>80</td><td>40.5</td><td>2</td><td>279</td><td>367</td><td>0.057</td><td>3.32</td><td>3.65</td><td>1.63</td><td>47</td><td>57</td><td>-712</td><td>-949</td><td>-2540</td><td>8</td><td>4</td><td>21</td><td>87</td><td>90</td><td>114</td><td>120</td><td>209</td><td>1.29E-05</td></tr>
<tr><td>5</td><td>1|6|1|1.25|0|1555|13.8|pf<2|r2<70</td><td>22739</td><td>20027</td><td>82</td><td>33.5</td><td>2.4</td><td>278</td><td>385</td><td>0.019</td><td>3.15</td><td>3.55</td><td>1.7</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-2829</td><td>9</td><td>5</td><td>18</td><td>89</td><td>92</td><td>94</td><td>127</td><td>243</td><td>1.41E-05</td></tr>
<tr><td>6</td><td>1|6|1|1.25|0|1555|13.8|pf<2|</td><td>23094</td><td>19962</td><td>74</td><td>29.5</td><td>2.5</td><td>313</td><td>388</td><td>0.003</td><td>3.17</td><td>3.36</td><td>1.69</td><td>44</td><td>57</td><td>-583</td><td>-1062</td><td>-3565</td><td>9</td><td>5</td><td>18</td><td>89</td><td>93</td><td>94</td><td>142</td><td>209</td><td>1.08E-04</td></tr>
<tr><td>7</td><td>1|7|1|1.5|0|1555|13.8|pf<3|r2<80</td><td>22360</td><td>19912</td><td>72</td><td>36.5</td><td>2</td><td>309</td><td>370</td><td>0.021</td><td>3.19</td><td>3.44</td><td>1.65</td><td>46</td><td>56</td><td>-712</td><td>-949</td><td>-2540</td><td>8</td><td>4</td><td>29</td><td>85</td><td>89</td><td>76</td><td>135</td><td>253</td><td>9.27E-05</td></tr>
<tr><td>8</td><td>1|7|1|1|0|1555|13.8|pf<4|</td><td>23357</td><td>19765</td><td>64</td><td>26</td><td>2.5</td><td>364</td><td>400</td><td>-0.095</td><td>3.89</td><td>3.06</td><td>1.64</td><td>44</td><td>60</td><td>-565</td><td>-1315</td><td>-4314</td><td>8</td><td>5</td><td>11</td><td>85</td><td>90</td><td>92</td><td>171</td><td>149</td><td>8.49E-04</td></tr>
<tr><td>9</td><td>2|11|1.5|3|0|1555|13.8|r2<80</td><td>20932</td><td>19624</td><td>89</td><td>64</td><td>1.4</td><td>236</td><td>403</td><td>-0.063</td><td>3.5</td><td>3.38</td><td>1.4</td><td>53</td><td>58</td><td>-1095</td><td>-1128</td><td>-1959</td><td>7</td><td>5</td><td>28</td><td>92</td><td>89</td><td>44</td><td>140</td><td>445</td><td>6.33E-07</td></tr>
<tr><td>10</td><td>2|11|1.5|3|0|1555|13.8|pf<5|r2<80</td><td>20932</td><td>19624</td><td>89</td><td>64</td><td>1.4</td><td>236</td><td>403</td><td>-0.063</td><td>3.5</td><td>3.38</td><td>1.4</td><td>53</td><td>58</td><td>-1095</td><td>-1128</td><td>-1959</td><td>7</td><td>5</td><td>28</td><td>92</td><td>89</td><td>44</td><td>140</td><td>445</td><td>6.33E-07</td></tr>
<tr><td>11</td><td>1|6|1|1.25|0|1555|13.8|r2<70</td><td>22337</td><td>19541</td><td>77</td><td>32</td><td>2.4</td><td>289</td><td>384</td><td>-0.02</td><td>3.23</td><td>3.42</td><td>1.68</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-2829</td><td>9</td><td>5</td><td>19</td><td>89</td><td>90</td><td>82</td><td>137</td><td>245</td><td>4.32E-05</td></tr>
<tr><td>12</td><td>1|6|1|1.25|0|1555|13.8|pf<4|r2<70</td><td>22337</td><td>19541</td><td>77</td><td>32</td><td>2.4</td><td>289</td><td>384</td><td>-0.02</td><td>3.23</td><td>3.42</td><td>1.68</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-2829</td><td>9</td><td>5</td><td>19</td><td>89</td><td>90</td><td>82</td><td>137</td><td>245</td><td>4.32E-05</td></tr>
<tr><td>13</td><td>1|6|1|1.25|0|1555|13.8|pf<3|r2<70</td><td>22337</td><td>19541</td><td>77</td><td>32</td><td>2.4</td><td>289</td><td>384</td><td>-0.02</td><td>3.23</td><td>3.42</td><td>1.68</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-2829</td><td>9</td><td>5</td><td>19</td><td>89</td><td>90</td><td>82</td><td>137</td><td>245</td><td>4.32E-05</td></tr>
<tr><td>14</td><td>1|6|1|1.25|0|1555|13.8|pf<5|r2<70</td><td>22337</td><td>19541</td><td>77</td><td>32</td><td>2.4</td><td>289</td><td>384</td><td>-0.02</td><td>3.23</td><td>3.42</td><td>1.68</td><td>45</td><td>57</td><td>-583</td><td>-1010</td><td>-2829</td><td>9</td><td>5</td><td>19</td><td>89</td><td>90</td><td>82</td><td>137</td><td>245</td><td>4.32E-05</td></tr>
<tr><td>15</td><td>2|10|1.75|2.25|0|1555|13.8|pf<2|</td><td>20891</td><td>19391</td><td>98</td><td>55.7</td><td>1.8</td><td>214</td><td>398</td><td>-0.203</td><td>3.2</td><td>3.59</td><td>1.6</td><td>49</td><td>58</td><td>-789</td><td>-1196</td><td>-1912</td><td>9</td><td>4</td><td>2</td><td>89</td><td>83</td><td>84</td><td>124</td><td>255</td><td>6.25E-08</td></tr>
</table>

Row 1 QQQ5Fixm20x1dxo is the PWFO output files abbreviation, First OOS Day End Date (2/1/22), Last OOS Day End Date (08/04/23), **Number of days**(#381) **a**=average of bootstrap random picks. **s**= standard deviation of bootstrap random picks. **f**=number of different filters examined. **c**= slippage and round-trip trade cost(c=$4).

The WFINP AVE File Output Cols are defined as follows.

- **Row 2 to Last Row Columns: A through AA**

  Col A: ***The Strategy Input/Filter Names***
  Row 9: **2|11|1.5|3|0|1555|13.8| r2<80**. This is constructed as follows. For the strategy inputs **2|11|1.5|3|0|1555|13.8|** only those in-sample sections that have **r2≤80** are used to trade in the following out-of-sample sections. If the in-sample r2>80, then the out-of-sample section following the in-sample section ***is not*** traded.
  Col B: ***toGP*** Total out-of-sample(oos) gross profit for these 381 oos periods (for this run periods = weeks).
  Col C: ***toNP*** Total out-of-sample(oos) Net profit (toGP-Number of Trade Weeks*cost) for the 381 oos periods.
  Col D: ***aoGP*** Average oos gross profit for the # oos periods
  Col E: ***aoTr*** Average oos profit per trade
  Col F: ***ao#T*** Average number of oos trades per week
  Col G: ***std*** The standard deviation of the # oos period profits and losses
  Col H: ***skew*** The Skew statistic of the # oos period profits and losses.
  Col I: ***kur*** The kurtosis statistic of the # oos period profits and losses
  Col J: ***t*** The student t statistic for the # oos periods. The higher the t statistic the higher the probability that this result was not due to pure chance.
  Col K: ***oW|oL*** Ratio of average oos winning trades divided by average oos losing trades.
  Col L: ***%Wtr*** The percentage if oos winning trades.
  Col M: ***%P*** percent of all oos periods that were profitable.
  Col N: ***LLtr*** The largest losing oos trade in all oos periods
  Col O: ***LLp*** The largest losing oos period
  Col P: ***eqDD*** The oos equity drawdown
  Col Q: ***wpr*** The largest number of winning oos periods (weeks) in a row.
  Col R: ***lpr*** The largest number of losing oos periods in a row.

Col S: ***#*** The number of oos periods this filter produced any profit or loss. Note for some oos periods there can be no strategy inputs that satisfy a given filters criteria, and no trades will be made during that period.
Col T: ***v20 The*** straight-line trend of the oos equity curve for the last 20 bars.
Col U: ***Dev^2*** A measure of equity curve smoothness. The square root of the average (equity curve minus a straight line)^2)
Col V: ***KTau*** The Kendall rank coefficient is often used as a test statistic in a statistical hypothesis test to establish whether two variables may be regarded as statistically dependent. This test is non-parametric, as it does not rely on any assumptions on the distributions of X or Y or the distribution of (X,Y)
Col W: ***eqR2*** The correlation coefficient(R^2) of a straight line fit to the equity curve.
Col X: ***Blw*** The maximum number of oos periods the oos equity curve failed to make a new high.
Col Y: ***BE*** Break even in oos periods. Assuming the average and standard deviation are from a normal distribution, this is the number of oos periods you would have to trade to have a 98% probability that your oos equity is above zero.
Col Z: ***tkr|bl*** =100*t*Ktau*eqR2/Blw/BE. This is measure of the best equity curve.
Col AA: ***Prob*** The probability that the filters oos toNP was due to pure chance. Row 1 lists the random the 5000-mirror filter's bootstrap average for our 381 out-of-sample files of **$1.2** with a bootstrap standard deviation of **$16.9**. (Side Note. The average is the average per out-of-sample period. So, the average for the random selection would be the random toNP/381 and the average for the filter would be the filter toNP/# of OOS periods traded or 19624/236=83.1). The probability of obtaining our filters average daily net profit **of 83.1** is **6.33 x10^{-7}** which is **4.85** standard deviations from the bootstrap average. For our filter, in row 4 above, the expected number of cases that we could obtain by pure chance that would match or exceed **$83.1** is [1-(1-**6.33 x10^{-7}**)^{564479}]**~ 564479*6.33 x10^{-7}** = **.357** where **564479** is the total number of different filters we looked at in this run. This number is less than one, so it is improbable that our result was due to pure chance.

Table 1 Walk Forward Out-Of-Sample Performance Summary for the QQQ 5-min FixmVn Strategy

QQQ-5 min bars 2/1/2022 - 8/4/2023.

Filter: **2|11|1.5|3|0|1555|13.8 |r2<85**: The inputs **2|11|1.5|3|0|1555|13.8** for all in-sample files that have **R2 ≤80.** are used to trade in the following out-of-sample sections.

IS-r2 = in-sample equity r2
osnp = Daily out-of-sample gross profit in $
NOnp$4 = Daily out-of-sample net profit in $ = **osnp-ont*4**.
ont = The number of trades in the out-of-sample day
ownp = winning profits in the out-of-sample day.
ownt = number of winning trades in the out-of-sample day
ollt = The largest losing trade in the out-of-sample day in $.
odd = The drawdown in the out-of-sample day in $.
EQ=Equity = Running Sum of daily out-of-sample gross profits $
NetEq=Net Equity = running sum of the daily out-of-sample net profits in $
Note: Blank rows indicate that no out-of-sample trades were made that day

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
02/01/22	2| 11| 1.5| 3| r2<80	-57	217	213	1	217	1	0	0	217	213
02/02/22	2| 11| 1.5| 3| r2<80	-53	(7)	(11)	1	0	0	-7	-7	210	202
02/03/22	2| 11| 1.5| 3| r2<80	-41	(756)	(764)	2	0	0	-665	-756	(546)	(562)
02/04/22	2| 11| 1.5| 3| r2<80	-33	398	394	1	398	1	0	0	(148)	(168)
02/07/22	2| 11| 1.5| 3| r2<80	-32	(680)	(684)	1	0	0	-680	-680	(828)	(852)
02/08/22	2| 11| 1.5| 3| r2<80	-24	369	365	1	369	1	0	0	(459)	(487)
02/09/22	2| 11| 1.5| 3| r2<80	-16	295	291	1	295	1	0	0	(164)	(196)
02/10/22	2| 11| 1.5| 3| r2<80	-7	(1128)	(1136)	2	0	0	-718	-1128	(1292)	(1332)
02/11/22	2| 11| 1.5| 3| r2<80	-6	270	266	1	270	1	0	0	(1022)	(1066)
02/14/22	2| 11| 1.5| 3| r2<80	-3	130	126	1	130	1	0	0	(892)	(940)
02/15/22	2| 11| 1.5| 3| r2<80	-4	226	222	1	226	1	0	0	(666)	(718)
02/16/22	2| 11| 1.5| 3| r2<80	0	392	384	2	443	1	-51	-51	(274)	(334)
02/17/22	2| 11| 1.5| 3| r2<80	1	0	0	0	0	0	0	0	(274)	(334)
02/18/22	2| 11| 1.5| 3| r2<80	0	(254)	(258)	1	0	0	-254	-254	(528)	(592)
02/22/22	2| 11| 1.5| 3| r2<80	-18	(600)	(604)	1	0	0	-600	-600	(1128)	(1196)
02/23/22	2| 11| 1.5| 3| r2<80	-15	394	386	2	817	1	-423	-423	(734)	(810)
02/24/22	2| 11| 1.5| 3| r2<80	-24	1509	1501	2	1711	1	-202	-202	775	691
02/25/22	2| 11| 1.5| 3| r2<80	-15	468	464	1	468	1	0	0	1243	1155
02/28/22	2| 11| 1.5| 3| r2<80	-1	47	43	1	47	1	0	0	1290	1198
03/01/22	2| 11| 1.5| 3| r2<80	2	0	0	0	0	0	0	0	1290	1198
03/02/22	2| 11| 1.5| 3| r2<80	4	(41)	(53)	3	414	1	-322	-455	1249	1145
03/03/22	2| 11| 1.5| 3| r2<80	28	0	0	0	0	0	0	0	1249	1145
03/04/22	2| 11| 1.5| 3| r2<80	38	(246)	(250)	1	0	0	-246	-246	1003	895
03/07/22	2| 11| 1.5| 3| r2<80	49	841	837	1	841	1	0	0	1844	1732
03/08/22	2| 11| 1.5| 3| r2<80	56	72	48	6	740	2	-282	-380	1916	1780
03/09/22	2| 11| 1.5| 3| r2<80	76	414	410	1	414	1	0	0	2330	2190
03/10/22	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	2330	2190
03/11/22	2| 11| 1.5| 3| r2<80	85	0	0	0	0	0	0	0	2330	2190
03/14/22	2| 11| 1.5| 3| r2<80	81	0	0	0	0	0	0	0	2330	2190
03/15/22	2| 11| 1.5| 3| r2<80	71	699	695	1	699	1	0	0	3029	2885
03/16/22	2| 11| 1.5| 3| r2<80	66	(87)	(99)	3	563	1	-354	-650	2942	2786
03/17/22	2| 11| 1.5| 3| r2<80	45	208	204	1	208	1	0	0	3150	2990

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
03/18/22	2| 11| 1.5| 3| r2<80	44	543	539	1	543	1	0	0	3693	3529
03/21/22	2| 11| 1.5| 3| r2<80	42	35	31	1	35	1	0	0	3728	3560
03/22/22	2| 11| 1.5| 3| r2<80	44	539	535	1	539	1	0	0	4267	4095
03/23/22	2| 11| 1.5| 3| r2<80	42	(283)	(291)	2	0	0	-167	-283	3984	3804
03/24/22	2| 11| 1.5| 3| r2<80	36	505	501	1	505	1	0	0	4489	4305
03/25/22	2| 11| 1.5| 3| r2<80	32	0	0	0	0	0	0	0	4489	4305
03/28/22	2| 11| 1.5| 3| r2<80	30	0	0	0	0	0	0	0	4489	4305
03/29/22	2| 11| 1.5| 3| r2<80	28	(781)	(789)	2	0	0	-402	-781	3708	3516
03/30/22	2| 11| 1.5| 3| r2<80	32	0	0	0	0	0	0	0	3708	3516
03/31/22	2| 11| 1.5| 3| r2<80	20	0	0	0	0	0	0	0	3708	3516
04/01/22	2| 11| 1.5| 3| r2<80	20	0	0	0	0	0	0	0	3708	3516
04/04/22	2| 11| 1.5| 3| r2<80	14	0	0	0	0	0	0	0	3708	3516
04/05/22	2| 11| 1.5| 3| r2<80	15	0	0	0	0	0	0	0	3708	3516
04/06/22	2| 11| 1.5| 3| r2<80	19	(335)	(355)	5	266	1	-258	-601	3373	3161
04/07/22	2| 11| 1.5| 3| r2<80	15	336	332	1	336	1	0	0	3709	3493
04/08/22	2| 11| 1.5| 3| r2<80	33	(142)	(150)	2	15	1	-157	-157	3567	3343
04/11/22	2| 11| 1.5| 3| r2<80	27	(505)	(513)	2	0	0	-420	-505	3062	2830
04/12/22	2| 11| 1.5| 3| r2<80	7	(486)	(490)	1	0	0	-486	-486	2576	2340
04/13/22	2| 11| 1.5| 3| r2<80	0	197	193	1	197	1	0	0	2773	2533
04/14/22	2| 11| 1.5| 3| r2<80	-37	0	0	0	0	0	0	0	2773	2533
04/18/22	2| 11| 1.5| 3| r2<80	-68	(212)	(216)	1	0	0	-212	-212	2561	2317
04/19/22	2| 11| 1.5| 3| r2<80	-81	570	566	1	570	1	0	0	3131	2883
04/20/22	2| 11| 1.5| 3| r2<80	-77	0	0	0	0	0	0	0	3131	2883
04/21/22	2| 11| 1.5| 3| r2<80	-76	813	805	2	1034	1	-221	-221	3944	3688
04/22/22	2| 11| 1.5| 3| r2<80	-41	(305)	(309)	1	0	0	-305	-305	3639	3379
04/25/22	2| 11| 1.5| 3| r2<80	-29	335	331	1	335	1	0	0	3974	3710
04/26/22	2| 11| 1.5| 3| r2<80	-15	(85)	(93)	2	340	1	-425	-425	3889	3617
04/27/22	2| 11| 1.5| 3| r2<80	0	(757)	(769)	3	0	0	-485	-757	3132	2848
04/28/22	2| 11| 1.5| 3| r2<80	0	565	561	1	565	1	0	0	3697	3409
04/29/22	2| 11| 1.5| 3| r2<80	0	544	536	2	919	1	-375	-375	4241	3945
05/02/22	2| 11| 1.5| 3| r2<80	0	657	645	3	795	2	-138	-138	4898	4590
05/03/22	2| 11| 1.5| 3| r2<80	12	(103)	(107)	1	0	0	-103	-103	4795	4483
05/04/22	2| 11| 1.5| 3| r2<80	17	1084	1080	1	1084	1	0	0	5879	5563
05/05/22	2| 11| 1.5| 3| r2<80	41	713	705	2	968	1	-255	-255	6592	6268
05/06/22	2| 11| 1.5| 3| r2<80	55	(128)	(136)	2	65	1	-193	-193	6464	6132
05/09/22	2| 11| 1.5| 3| r2<80	71	868	864	1	868	1	0	0	7332	6996
05/10/22	2| 11| 1.5| 3| r2<80	78	59	47	3	317	2	-258	-258	7391	7043
05/11/22	2| 11| 1.5| 3| r2<80	83	0	0	0	0	0	0	0	7391	7043
05/12/22	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	7391	7043
05/13/22	2| 11| 1.5| 3| r2<80	80	655	651	1	655	1	0	0	8046	7694
05/16/22	2| 11| 1.5| 3| r2<80	81	0	0	0	0	0	0	0	8046	7694
05/17/22	2| 11| 1.5| 3| r2<80	80	305	293	3	486	2	-181	-181	8351	7987
05/18/22	2| 11| 1.5| 3| r2<80	80	(1084)	(1092)	2	11	1	-1095	-1095	7267	6895
05/19/22	2| 11| 1.5| 3| r2<80	78	(156)	(160)	1	0	0	-156	-156	7111	6735
05/20/22	2| 11| 1.5| 3| r2<80	73	1136	1124	3	1355	2	-219	-219	8247	7859
05/23/22	2| 11| 1.5| 3| r2<80	67	215	211	1	215	1	0	0	8462	8070
05/24/22	2| 11| 1.5| 3| r2<80	66	540	532	2	540	2	0	0	9002	8602
05/25/22	2| 11| 1.5| 3| r2<80	67	99	95	1	99	1	0	0	9101	8697
05/26/22	2| 11| 1.5| 3| r2<80	60	630	626	1	630	1	0	0	9731	9323
05/27/22	2| 11| 1.5| 3| r2<80	60	493	489	1	493	1	0	0	10224	9812
05/31/22	2| 11| 1.5| 3| r2<80	44	175	171	1	175	1	0	0	10399	9983
06/01/22	2| 11| 1.5| 3| r2<80	44	(292)	(304)	3	101	1	-213	-292	10107	9679
06/02/22	2| 11| 1.5| 3| r2<80	54	600	596	1	600	1	0	0	10707	10275
06/03/22	2| 11| 1.5| 3| r2<80	59	(297)	(305)	2	2	1	-299	-299	10410	9970
06/06/22	2| 11| 1.5| 3| r2<80	64	(330)	(334)	1	0	0	-330	-330	10080	9636
06/07/22	2| 11| 1.5| 3| r2<80	69	256	252	1	256	1	0	0	10336	9888
06/08/22	2| 11| 1.5| 3| r2<80	80	0	0	0	0	0	0	0	10336	9888
06/09/22	2| 11| 1.5| 3| r2<80	79	(784)	(788)	1	0	0	-784	-784	9552	9100

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
06/10/22	2| 11| 1.5| 3| r2<80	71	287	283	1	287	1	0	0	9839	9383
06/13/22	2| 11| 1.5| 3| r2<80	70	(321)	(329)	2	123	1	-444	-444	9518	9054
06/14/22	2| 11| 1.5| 3| r2<80	64	(43)	(47)	1	0	0	-43	-43	9475	9007
06/15/22	2| 11| 1.5| 3| r2<80	55	310	306	1	310	1	0	0	9785	9313
06/16/22	2| 11| 1.5| 3| r2<80	46	(105)	(113)	2	139	1	-244	-244	9680	9200
06/17/22	2| 11| 1.5| 3| r2<80	34	116	112	1	116	1	0	0	9796	9312
06/20/22	2| 11| 1.5| 3| r2<80	8	0	0	0	0	0	0	0	9796	9312
06/21/22	2| 11| 1.5| 3| r2<80	2	176	172	1	176	1	0	0	9972	9484
06/22/22	2| 11| 1.5| 3| r2<80	-7	11	7	1	11	1	0	0	9983	9491
06/23/22	2| 11| 1.5| 3| r2<80	-26	0	0	0	0	0	0	0	9983	9491
06/24/22	2| 11| 1.5| 3| r2<80	-39	508	504	1	508	1	0	0	10491	9995
06/27/22	2| 11| 1.5| 3| r2<80	-22	(282)	(286)	1	0	0	-282	-282	10209	9709
06/28/22	2| 11| 1.5| 3| r2<80	-16	542	534	2	813	1	-271	-271	10751	10243
06/29/22	2| 11| 1.5| 3| r2<80	-3	(38)	(42)	1	0	0	-38	-38	10713	10201
06/30/22	2| 11| 1.5| 3| r2<80	0	345	337	2	345	2	0	0	11058	10538
07/01/22	2| 11| 1.5| 3| r2<80	17	54	50	1	54	1	0	0	11112	10588
07/05/22	2| 11| 1.5| 3| r2<80	60	719	711	2	845	1	-126	-126	11831	11299
07/06/22	2| 11| 1.5| 3| r2<80	80	(170)	(174)	1	0	0	-170	-170	11661	11125
07/07/22	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	11661	11125
07/08/22	2| 11| 1.5| 3| r2<80	84	0	0	0	0	0	0	0	11661	11125
07/11/22	2| 11| 1.5| 3| r2<80	88	0	0	0	0	0	0	0	11661	11125
07/12/22	2| 11| 1.5| 3| r2<80	93	0	0	0	0	0	0	0	11661	11125
07/13/22	2| 11| 1.5| 3| r2<80	83	0	0	0	0	0	0	0	11661	11125
07/14/22	2| 11| 1.5| 3| r2<80	78	(556)	(560)	1	0	0	-556	-556	11105	10565
07/15/22	2| 11| 1.5| 3| r2<80	61	74	70	1	74	1	0	0	11179	10635
07/18/22	2| 11| 1.5| 3| r2<80	46	(562)	(566)	1	0	0	-562	-562	10617	10069
07/19/22	2| 11| 1.5| 3| r2<80	31	550	546	1	550	1	0	0	11167	10615
07/20/22	2| 11| 1.5| 3| r2<80	20	177	173	1	177	1	0	0	11344	10788
07/21/22	2| 11| 1.5| 3| r2<80	11	312	308	1	312	1	0	0	11656	11096
07/22/22	2| 11| 1.5| 3| r2<80	12	0	0	0	0	0	0	0	11656	11096
07/25/22	2| 11| 1.5| 3| r2<80	8	0	0	0	0	0	0	0	11656	11096
07/26/22	2| 11| 1.5| 3| r2<80	3	0	0	0	0	0	0	0	11656	11096
07/27/22	2| 11| 1.5| 3| r2<80	-1	859	855	1	859	1	0	0	12515	11951
07/28/22	2| 11| 1.5| 3| r2<80	0	449	445	1	449	1	0	0	12964	12396
07/29/22	2| 11| 1.5| 3| r2<80	0	327	323	1	327	1	0	0	13291	12719
08/01/22	2| 11| 1.5| 3| r2<80	1	(94)	(98)	1	0	0	-94	-94	13197	12621
08/02/22	2| 11| 1.5| 3| r2<80	5	(150)	(154)	1	0	0	-150	-150	13047	12467
08/03/22	2| 11| 1.5| 3| r2<80	8	520	516	1	520	1	0	0	13567	12983
08/04/22	2| 11| 1.5| 3| r2<80	15	0	0	0	0	0	0	0	13567	12983
08/05/22	2| 11| 1.5| 3| r2<80	19	(54)	(58)	1	0	0	-54	-54	13513	12925
08/08/22	2| 11| 1.5| 3| r2<80	34	(306)	(310)	1	0	0	-306	-306	13207	12615
08/09/22	2| 11| 1.5| 3| r2<80	62	(29)	(33)	1	0	0	-29	-29	13178	12582
08/10/22	2| 11| 1.5| 3| r2<80	78	(338)	(346)	2	0	0	-288	-338	12840	12236
08/11/22	2| 11| 1.5| 3| r2<80	71	(386)	(390)	1	0	0	-386	-386	12454	11846
08/12/22	2| 11| 1.5| 3| r2<80	55	431	427	1	431	1	0	0	12885	12273
08/15/22	2| 11| 1.5| 3| r2<80	44	0	0	0	0	0	0	0	12885	12273
08/16/22	2| 11| 1.5| 3| r2<80	33	0	0	0	0	0	0	0	12885	12273
08/17/22	2| 11| 1.5| 3| r2<80	21	(79)	(87)	2	0	0	-43	-79	12806	12186
08/18/22	2| 11| 1.5| 3| r2<80	2	0	0	0	0	0	0	0	12806	12186
08/19/22	2| 11| 1.5| 3| r2<80	-8	274	270	1	274	1	0	0	13080	12456
08/22/22	2| 11| 1.5| 3| r2<80	-5	(233)	(241)	2	47	1	-280	-280	12847	12215
08/23/22	2| 11| 1.5| 3| r2<80	-5	0	0	0	0	0	0	0	12847	12215
08/24/22	2| 11| 1.5| 3| r2<80	-5	0	0	0	0	0	0	0	12847	12215
08/25/22	2| 11| 1.5| 3| r2<80	-23	207	203	1	207	1	0	0	13054	12418
08/26/22	2| 11| 1.5| 3| r2<80	-27	749	745	1	749	1	0	0	13803	13163
08/29/22	2| 11| 1.5| 3| r2<80	-2	0	0	0	0	0	0	0	13803	13163
08/30/22	2| 11| 1.5| 3| r2<80	-1	(96)	(100)	1	0	0	-96	-96	13707	13063
08/31/22	2| 11| 1.5| 3| r2<80	0	(244)	(248)	1	0	0	-244	-244	13463	12815

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
09/01/22	2| 11| 1.5| 3| r2<80	10	207	199	2	207	2	0	0	13670	13014
09/02/22	2| 11| 1.5| 3| r2<80	21	(727)	(731)	1	0	0	-727	-727	12943	12283
09/06/22	2| 11| 1.5| 3| r2<80	33	(33)	(37)	1	0	0	-33	-33	12910	12246
09/07/22	2| 11| 1.5| 3| r2<80	27	428	424	1	428	1	0	0	13338	12670
09/08/22	2| 11| 1.5| 3| r2<80	30	135	131	1	135	1	0	0	13473	12801
09/09/22	2| 11| 1.5| 3| r2<80	22	333	329	1	333	1	0	0	13806	13130
09/12/22	2| 11| 1.5| 3| r2<80	26	0	0	0	0	0	0	0	13806	13130
09/13/22	2| 11| 1.5| 3| r2<80	26	(450)	(458)	2	188	1	-638	-638	13356	12672
09/14/22	2| 11| 1.5| 3| r2<80	32	62	58	1	62	1	0	0	13418	12730
09/15/22	2| 11| 1.5| 3| r2<80	15	(112)	(116)	1	0	0	-112	-112	13306	12614
09/16/22	2| 11| 1.5| 3| r2<80	11	2	(6)	2	138	1	-136	-136	13308	12608
09/19/22	2| 11| 1.5| 3| r2<80	2	0	0	0	0	0	0	0	13308	12608
09/20/22	2| 11| 1.5| 3| r2<80	-1	0	0	0	0	0	0	0	13308	12608
09/21/22	2| 11| 1.5| 3| r2<80	-1	309	297	3	549	2	-240	-240	13617	12905
09/22/22	2| 11| 1.5| 3| r2<80	-3	(85)	(89)	1	0	0	-85	-85	13532	12816
09/23/22	2| 11| 1.5| 3| r2<80	-6	98	90	2	103	1	-5	-5	13630	12906
09/26/22	2| 11| 1.5| 3| r2<80	0	0	0	0	0	0	0	0	13630	12906
09/27/22	2| 11| 1.5| 3| r2<80	0	(164)	(176)	3	140	1	-271	-271	13466	12730
09/28/22	2| 11| 1.5| 3| r2<80	1	447	443	1	447	1	0	0	13913	13173
09/29/22	2| 11| 1.5| 3| r2<80	6	366	362	1	366	1	0	0	14279	13535
09/30/22	2| 11| 1.5| 3| r2<80	23	0	0	0	0	0	0	0	14279	13535
10/03/22	2| 11| 1.5| 3| r2<80	17	354	350	1	354	1	0	0	14633	13885
10/04/22	2| 11| 1.5| 3| r2<80	27	187	183	1	187	1	0	0	14820	14068
10/05/22	2| 11| 1.5| 3| r2<80	31	0	0	0	0	0	0	0	14820	14068
10/06/22	2| 11| 1.5| 3| r2<80	30	(128)	(136)	2	0	0	-71	-128	14692	13932
10/07/22	2| 11| 1.5| 3| r2<80	46	(116)	(124)	2	235	1	-351	-351	14576	13808
10/10/22	2| 11| 1.5| 3| r2<80	63	(99)	(103)	1	0	0	-99	-99	14477	13705
10/11/22	2| 11| 1.5| 3| r2<80	64	0	0	0	0	0	0	0	14477	13705
10/12/22	2| 11| 1.5| 3| r2<80	78	0	0	0	0	0	0	0	14477	13705
10/13/22	2| 11| 1.5| 3| r2<80	80	893	885	2	1137	1	-244	-244	15370	14590
10/14/22	2| 11| 1.5| 3| r2<80	79	(345)	(353)	2	340	1	-685	-685	15025	14237
10/17/22	2| 11| 1.5| 3| r2<80	78	376	364	3	376	3	0	0	15401	14601
10/18/22	2| 11| 1.5| 3| r2<80	84	0	0	0	0	0	0	0	15401	14601
10/19/22	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	15401	14601
10/20/22	2| 11| 1.5| 3| r2<80	72	(422)	(426)	1	0	0	-422	-422	14979	14175
10/21/22	2| 11| 1.5| 3| r2<80	57	490	486	1	490	1	0	0	15469	14661
10/24/22	2| 11| 1.5| 3| r2<80	45	349	345	1	349	1	0	0	15818	15006
10/25/22	2| 11| 1.5| 3| r2<80	47	336	332	1	336	1	0	0	16154	15338
10/26/22	2| 11| 1.5| 3| r2<80	29	(285)	(293)	2	0	0	-154	-285	15869	15045
10/27/22	2| 11| 1.5| 3| r2<80	27	(423)	(427)	1	0	0	-423	-423	15446	14618
10/28/22	2| 11| 1.5| 3| r2<80	16	585	581	1	585	1	0	0	16031	15199
10/31/22	2| 11| 1.5| 3| r2<80	20	0	0	0	0	0	0	0	16031	15199
11/01/22	2| 11| 1.5| 3| r2<80	18	(796)	(808)	3	0	0	-451	-796	15235	14391
11/02/22	2| 11| 1.5| 3| r2<80	6	439	431	2	750	1	-311	-311	15674	14822
11/03/22	2| 11| 1.5| 3| r2<80	1	(165)	(173)	2	0	0	-144	-165	15509	14649
11/04/22	2| 11| 1.5| 3| r2<80	0	(67)	(71)	1	0	0	-67	-67	15442	14578
11/07/22	2| 11| 1.5| 3| r2<80	0	0	0	0	0	0	0	0	15442	14578
11/08/22	2| 11| 1.5| 3| r2<80	-2	183	179	1	183	1	0	0	15625	14757
11/09/22	2| 11| 1.5| 3| r2<80	-2	(596)	(604)	2	0	0	-485	-596	15029	14153
11/10/22	2| 11| 1.5| 3| r2<80	-5	(316)	(324)	2	197	1	-513	-513	14713	13829
11/11/22	2| 11| 1.5| 3| r2<80	-22	0	0	0	0	0	0	0	14713	13829
11/14/22	2| 11| 1.5| 3| r2<80	-29	(81)	(85)	1	0	0	-81	-81	14632	13744
11/15/22	2| 11| 1.5| 3| r2<80	-24	(330)	(334)	1	0	0	-330	-330	14302	13410
11/16/22	2| 11| 1.5| 3| r2<80	-33	0	0	0	0	0	0	0	14302	13410
11/17/22	2| 11| 1.5| 3| r2<80	-38	94	86	2	168	1	-74	-74	14396	13496
11/18/22	2| 11| 1.5| 3| r2<80	-66	(201)	(205)	1	0	0	-201	-201	14195	13291
11/21/22	2| 11| 1.5| 3| r2<80	-75	0	0	0	0	0	0	0	14195	13291
11/22/22	2| 11| 1.5| 3| r2<80	-75	321	317	1	321	1	0	0	14516	13608

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
11/23/22	2| 11| 1.5| 3| r2<80	-74	0	0	0	0	0	0	0	14516	13608
11/25/22	2| 11| 1.5| 3| r2<80	-71	0	0	0	0	0	0	0	14516	13608
11/28/22	2| 11| 1.5| 3| r2<80	-66	0	0	0	0	0	0	0	14516	13608
11/29/22	2| 11| 1.5| 3| r2<80	-66	0	0	0	0	0	0	0	14516	13608
11/30/22	2| 11| 1.5| 3| r2<80	-70	780	776	1	780	1	0	0	15296	14384
12/01/22	2| 11| 1.5| 3| r2<80	-56	(326)	(338)	3	135	1	-328	-461	14970	14046
12/02/22	2| 11| 1.5| 3| r2<80	-19	263	255	2	263	2	0	0	15233	14301
12/05/22	2| 11| 1.5| 3| r2<80	-3	0	0	0	0	0	0	0	15233	14301
12/06/22	2| 11| 1.5| 3| r2<80	-3	0	0	0	0	0	0	0	15233	14301
12/07/22	2| 11| 1.5| 3| r2<80	0	(136)	(140)	1	0	0	-136	-136	15097	14161
12/08/22	2| 11| 1.5| 3| r2<80	21	62	58	1	62	1	0	0	15159	14219
12/09/22	2| 11| 1.5| 3| r2<80	63	0	0	0	0	0	0	0	15159	14219
12/12/22	2| 11| 1.5| 3| r2<80	63	0	0	0	0	0	0	0	15159	14219
12/13/22	2| 11| 1.5| 3| r2<80	70	554	542	3	568	2	-14	-14	15713	14761
12/14/22	2| 11| 1.5| 3| r2<80	77	(209)	(217)	2	0	0	-155	-209	15504	14544
12/15/22	2| 11| 1.5| 3| r2<80	79	464	460	1	464	1	0	0	15968	15004
12/16/22	2| 11| 1.5| 3| r2<80	75	0	0	0	0	0	0	0	15968	15004
12/19/22	2| 11| 1.5| 3| r2<80	71	0	0	0	0	0	0	0	15968	15004
12/20/22	2| 11| 1.5| 3| r2<80	71	46	42	1	46	1	0	0	16014	15046
12/21/22	2| 11| 1.5| 3| r2<80	71	0	0	0	0	0	0	0	16014	15046
12/22/22	2| 11| 1.5| 3| r2<80	71	153	149	1	153	1	0	0	16167	15195
12/23/22	2| 11| 1.5| 3| r2<80	76	73	69	1	73	1	0	0	16240	15264
12/27/22	2| 11| 1.5| 3| r2<80	80	(114)	(118)	1	0	0	-114	-114	16126	15146
12/28/22	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	16126	15146
12/29/22	2| 11| 1.5| 3| r2<80	90	0	0	0	0	0	0	0	16126	15146
12/30/22	2| 11| 1.5| 3| r2<80	90	0	0	0	0	0	0	0	16126	15146
01/02/23	2| 11| 1.5| 3| r2<80	91	0	0	0	0	0	0	0	16126	15146
01/03/23	2| 11| 1.5| 3| r2<80	91	0	0	0	0	0	0	0	16126	15146
01/04/23	2| 11| 1.5| 3| r2<80	83	0	0	0	0	0	0	0	16126	15146
01/05/23	2| 11| 1.5| 3| r2<80	76	(201)	(205)	1	0	0	-201	-201	15925	14941
01/06/23	2| 11| 1.5| 3| r2<80	60	442	438	1	442	1	0	0	16367	15379
01/09/23	2| 11| 1.5| 3| r2<80	63	(87)	(91)	1	0	0	-87	-87	16280	15288
01/10/23	2| 11| 1.5| 3| r2<80	64	111	107	1	111	1	0	0	16391	15395
01/11/23	2| 11| 1.5| 3| r2<80	52	278	274	1	278	1	0	0	16669	15669
01/12/23	2| 11| 1.5| 3| r2<80	43	86	82	1	86	1	0	0	16755	15751
01/13/23	2| 11| 1.5| 3| r2<80	46	243	239	1	243	1	0	0	16998	15990
01/17/23	2| 11| 1.5| 3| r2<80	55	(140)	(144)	1	0	0	-140	-140	16858	15846
01/18/23	2| 11| 1.5| 3| r2<80	57	(495)	(499)	1	0	0	-495	-495	16363	15347
01/19/23	2| 11| 1.5| 3| r2<80	49	0	0	0	0	0	0	0	16363	15347
01/20/23	2| 11| 1.5| 3| r2<80	46	521	517	1	521	1	0	0	16884	15864
01/23/23	2| 11| 1.5| 3| r2<80	52	361	357	1	361	1	0	0	17245	16221
01/24/23	2| 11| 1.5| 3| r2<80	60	0	0	0	0	0	0	0	17245	16221
01/25/23	2| 11| 1.5| 3| r2<80	56	753	745	2	753	2	0	0	17998	16966
01/26/23	2| 11| 1.5| 3| r2<80	66	117	113	1	117	1	0	0	18115	17079
01/27/23	2| 11| 1.5| 3| r2<80	74	0	0	0	0	0	0	0	18115	17079
01/30/23	2| 11| 1.5| 3| r2<80	81	0	0	0	0	0	0	0	18115	17079
01/31/23	2| 11| 1.5| 3| r2<80	84	0	0	0	0	0	0	0	18115	17079
02/01/23	2| 11| 1.5| 3| r2<80	83	0	0	0	0	0	0	0	18115	17079
02/02/23	2| 11| 1.5| 3| r2<80	83	0	0	0	0	0	0	0	18115	17079
02/03/23	2| 11| 1.5| 3| r2<80	68	(286)	(290)	1	0	0	-286	-286	17829	16789
02/06/23	2| 11| 1.5| 3| r2<80	54	(74)	(78)	1	0	0	-74	-74	17755	16711
02/07/23	2| 11| 1.5| 3| r2<80	37	485	473	3	700	2	-215	-215	18240	17184
02/08/23	2| 11| 1.5| 3| r2<80	13	0	0	0	0	0	0	0	18240	17184
02/09/23	2| 11| 1.5| 3| r2<80	8	(587)	(591)	1	0	0	-587	-587	17653	16593
02/10/23	2| 11| 1.5| 3| r2<80	1	(111)	(115)	1	0	0	-111	-111	17542	16478
02/13/23	2| 11| 1.5| 3| r2<80	0	0	0	0	0	0	0	0	17542	16478
02/14/23	2| 11| 1.5| 3| r2<80	0	15	3	3	340	1	-251	-325	17557	16481
02/15/23	2| 11| 1.5| 3| r2<80	-14	0	0	0	0	0	0	0	17557	16481

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
02/16/23	2| 11| 1.5| 3| r2<80	-38	(264)	(272)	2	0	0	-187	-264	17293	16209
02/17/23	2| 11| 1.5| 3| r2<80	-46	(18)	(26)	2	66	1	-84	-84	17275	16183
02/21/23	2| 11| 1.5| 3| r2<80	-79	0	0	0	0	0	0	0	17275	16183
02/22/23	2| 11| 1.5| 3| r2<80	-79	0	0	0	0	0	0	0	17275	16183
02/23/23	2| 11| 1.5| 3| r2<80	-82	(50)	(54)	1	0	0	-50	-50	17225	16129
02/24/23	2| 11| 1.5| 3| r2<80	-80	252	244	2	252	2	0	0	17477	16373
02/27/23	2| 11| 1.5| 3| r2<80	-74	(117)	(121)	1	0	0	-117	-117	17360	16252
02/28/23	2| 11| 1.5| 3| r2<80	-67	0	0	0	0	0	0	0	17360	16252
03/01/23	2| 11| 1.5| 3| r2<80	-67	(158)	(162)	1	0	0	-158	-158	17202	16090
03/02/23	2| 11| 1.5| 3| r2<80	-64	353	349	1	353	1	0	0	17555	16439
03/03/23	2| 11| 1.5| 3| r2<80	-36	277	273	1	277	1	0	0	17832	16712
03/06/23	2| 11| 1.5| 3| r2<80	-13	(159)	(163)	1	0	0	-159	-159	17673	16549
03/07/23	2| 11| 1.5| 3| r2<80	-4	(484)	(492)	2	0	0	-299	-484	17189	16057
03/08/23	2| 11| 1.5| 3| r2<80	1	0	0	0	0	0	0	0	17189	16057
03/09/23	2| 11| 1.5| 3| r2<80	1	0	0	0	0	0	0	0	17189	16057
03/10/23	2| 11| 1.5| 3| r2<80	5	(368)	(372)	1	0	0	-368	-368	16821	15685
03/13/23	2| 11| 1.5| 3| r2<80	0	153	149	1	153	1	0	0	16974	15834
03/14/23	2| 11| 1.5| 3| r2<80	-2	51	47	1	51	1	0	0	17025	15881
03/15/23	2| 11| 1.5| 3| r2<80	-8	0	0	0	0	0	0	0	17025	15881
03/16/23	2| 11| 1.5| 3| r2<80	-8	519	515	1	519	1	0	0	17544	16396
03/17/23	2| 11| 1.5| 3| r2<80	-2	0	0	0	0	0	0	0	17544	16396
03/20/23	2| 11| 1.5| 3| r2<80	-8	0	0	0	0	0	0	0	17544	16396
03/21/23	2| 11| 1.5| 3| r2<80	-8	169	165	1	169	1	0	0	17713	16561
03/22/23	2| 11| 1.5| 3| r2<80	-1	(436)	(444)	2	0	0	-339	-436	17277	16117
03/23/23	2| 11| 1.5| 3| r2<80	0	(4)	(8)	1	0	0	-4	-4	17273	16109
03/24/23	2| 11| 1.5| 3| r2<80	-2	120	116	1	120	1	0	0	17393	16225
03/27/23	2| 11| 1.5| 3| r2<80	-1	0	0	0	0	0	0	0	17393	16225
03/28/23	2| 11| 1.5| 3| r2<80	-1	0	0	0	0	0	0	0	17393	16225
03/29/23	2| 11| 1.5| 3| r2<80	-1	160	156	1	160	1	0	0	17553	16381
03/30/23	2| 11| 1.5| 3| r2<80	-1	0	0	0	0	0	0	0	17553	16381
03/31/23	2| 11| 1.5| 3| r2<80	0	0	0	0	0	0	0	0	17553	16381
04/03/23	2| 11| 1.5| 3| r2<80	3	0	0	0	0	0	0	0	17553	16381
04/04/23	2| 11| 1.5| 3| r2<80	17	0	0	0	0	0	0	0	17553	16381
04/05/23	2| 11| 1.5| 3| r2<80	36	0	0	0	0	0	0	0	17553	16381
04/06/23	2| 11| 1.5| 3| r2<80	36	328	324	1	328	1	0	0	17881	16705
04/10/23	2| 11| 1.5| 3| r2<80	35	344	336	2	344	2	0	0	18225	17041
04/11/23	2| 11| 1.5| 3| r2<80	49	0	0	0	0	0	0	0	18225	17041
04/12/23	2| 11| 1.5| 3| r2<80	35	0	0	0	0	0	0	0	18225	17041
04/13/23	2| 11| 1.5| 3| r2<80	35	325	321	1	325	1	0	0	18550	17362
04/14/23	2| 11| 1.5| 3| r2<80	56	0	0	0	0	0	0	0	18550	17362
04/17/23	2| 11| 1.5| 3| r2<80	56	0	0	0	0	0	0	0	18550	17362
04/18/23	2| 11| 1.5| 3| r2<80	56	(180)	(184)	1	0	0	-180	-180	18370	17178
04/19/23	2| 11| 1.5| 3| r2<80	79	0	0	0	0	0	0	0	18370	17178
04/20/23	2| 11| 1.5| 3| r2<80	94	0	0	0	0	0	0	0	18370	17178
04/21/23	2| 11| 1.5| 3| r2<80	92	0	0	0	0	0	0	0	18370	17178
04/24/23	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	18370	17178
04/25/23	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	18370	17178
04/26/23	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	18370	17178
04/27/23	2| 11| 1.5| 3| r2<80	52	524	520	1	524	1	0	0	18894	17698
04/28/23	2| 11| 1.5| 3| r2<80	68	88	84	1	88	1	0	0	18982	17782
05/01/23	2| 11| 1.5| 3| r2<80	77	0	0	0	0	0	0	0	18982	17782
05/02/23	2| 11| 1.5| 3| r2<80	77	0	0	0	0	0	0	0	18982	17782
05/03/23	2| 11| 1.5| 3| r2<80	77	0	0	0	0	0	0	0	18982	17782
05/04/23	2| 11| 1.5| 3| r2<80	77	0	0	0	0	0	0	0	18982	17782
05/05/23	2| 11| 1.5| 3| r2<80	69	407	403	1	407	1	0	0	19389	18185
05/08/23	2| 11| 1.5| 3| r2<80	77	0	0	0	0	0	0	0	19389	18185
05/09/23	2| 11| 1.5| 3| r2<80	62	0	0	0	0	0	0	0	19389	18185
05/10/23	2| 11| 1.5| 3| r2<80	62	18	14	1	18	1	0	0	19407	18199

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
05/11/23	2| 11| 1.5| 3| r2<80	73	0	0	0	0	0	0	0	19407	18199
05/12/23	2| 11| 1.5| 3| r2<80	87	0	0	0	0	0	0	0	19407	18199
05/15/23	2| 11| 1.5| 3| r2<80	87	0	0	0	0	0	0	0	19407	18199
05/16/23	2| 11| 1.5| 3| r2<80	87	0	0	0	0	0	0	0	19407	18199
05/17/23	2| 11| 1.5| 3| r2<80	89	0	0	0	0	0	0	0	19407	18199
05/18/23	2| 11| 1.5| 3| r2<80	89	0	0	0	0	0	0	0	19407	18199
05/19/23	2| 11| 1.5| 3| r2<80	89	0	0	0	0	0	0	0	19407	18199
05/22/23	2| 11| 1.5| 3| r2<80	91	0	0	0	0	0	0	0	19407	18199
05/23/23	2| 11| 1.5| 3| r2<80	91	0	0	0	0	0	0	0	19407	18199
05/24/23	2| 11| 1.5| 3| r2<80	91	0	0	0	0	0	0	0	19407	18199
05/25/23	2| 11| 1.5| 3| r2<80	88	0	0	0	0	0	0	0	19407	18199
05/26/23	2| 11| 1.5| 3| r2<80	88	0	0	0	0	0	0	0	19407	18199
05/30/23	2| 11| 1.5| 3| r2<80	81	0	0	0	0	0	0	0	19407	18199
05/31/23	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	19407	18199
06/01/23	2| 11| 1.5| 3| r2<80	82	0	0	0	0	0	0	0	19407	18199
06/02/23	2| 11| 1.5| 3| r2<80	87	0	0	0	0	0	0	0	19407	18199
06/05/23	2| 11| 1.5| 3| r2<80	35	0	0	0	0	0	0	0	19407	18199
06/06/23	2| 11| 1.5| 3| r2<80	35	0	0	0	0	0	0	0	19407	18199
06/07/23	2| 11| 1.5| 3| r2<80	35	(779)	(783)	1	0	0	-779	-779	18628	17416
06/08/23	2| 11| 1.5| 3| r2<80	-10	283	279	1	283	1	0	0	18911	17695
06/09/23	2| 11| 1.5| 3| r2<80	-22	(130)	(134)	1	0	0	-130	-130	18781	17561
06/12/23	2| 11| 1.5| 3| r2<80	-34	388	384	1	388	1	0	0	19169	17945
06/13/23	2| 11| 1.5| 3| r2<80	-32	(46)	(50)	1	0	0	-46	-46	19123	17895
06/14/23	2| 11| 1.5| 3| r2<80	-31	148	144	1	148	1	0	0	19271	18039
06/15/23	2| 11| 1.5| 3| r2<80	-26	0	0	0	0	0	0	0	19271	18039
06/16/23	2| 11| 1.5| 3| r2<80	-26	0	0	0	0	0	0	0	19271	18039
06/20/23	2| 11| 1.5| 3| r2<80	-26	0	0	0	0	0	0	0	19271	18039
06/21/23	2| 11| 1.5| 3| r2<80	-26	0	0	0	0	0	0	0	19271	18039
06/22/23	2| 11| 1.5| 3| r2<80	-26	0	0	0	0	0	0	0	19271	18039
06/23/23	2| 11| 1.5| 3| r2<80	-43	22	14	2	56	1	-34	-34	19293	18053
06/26/23	2| 11| 1.5| 3| r2<80	-23	0	0	0	0	0	0	0	19293	18053
06/27/23	2| 11| 1.5| 3| r2<80	-23	369	365	1	369	1	0	0	19662	18418
06/28/23	2| 11| 1.5| 3| r2<80	-1	(183)	(187)	1	0	0	-183	-183	19479	18231
06/29/23	2| 11| 1.5| 3| r2<80	0	0	0	0	0	0	0	0	19479	18231
06/30/23	2| 11| 1.5| 3| r2<80	11	254	250	1	254	1	0	0	19733	18481
07/03/23	2| 11| 1.5| 3| r2<80	90	0	0	0	0	0	0	0	19733	18481
07/05/23	2| 11| 1.5| 3| r2<80	90	0	0	0	0	0	0	0	19733	18481
07/06/23	2| 11| 1.5| 3| r2<80	86	0	0	0	0	0	0	0	19733	18481
07/07/23	2| 11| 1.5| 3| r2<80	81	0	0	0	0	0	0	0	19733	18481
07/10/23	2| 11| 1.5| 3| r2<80	76	(55)	(59)	1	0	0	-55	-55	19678	18422
07/11/23	2| 11| 1.5| 3| r2<80	63	0	0	0	0	0	0	0	19678	18422
07/12/23	2| 11| 1.5| 3| r2<80	50	57	53	1	57	1	0	0	19735	18475
07/13/23	2| 11| 1.5| 3| r2<80	35	322	318	1	322	1	0	0	20057	18793
07/14/23	2| 11| 1.5| 3| r2<80	53	0	0	0	0	0	0	0	20057	18793
07/17/23	2| 11| 1.5| 3| r2<80	53	221	217	1	221	1	0	0	20278	19010
07/18/23	2| 11| 1.5| 3| r2<80	66	306	302	1	306	1	0	0	20584	19312
07/19/23	2| 11| 1.5| 3| r2<80	73	0	0	0	0	0	0	0	20584	19312
07/20/23	2| 11| 1.5| 3| r2<80	73	0	0	0	0	0	0	0	20584	19312
07/21/23	2| 11| 1.5| 3| r2<80	73	(384)	(388)	1	0	0	-384	-384	20200	18924
07/24/23	2| 11| 1.5| 3| r2<80	59	(91)	(95)	1	0	0	-91	-91	20109	18829
07/25/23	2| 11| 1.5| 3| r2<80	53	192	188	1	192	1	0	0	20301	19017
07/26/23	2| 11| 1.5| 3| r2<80	60	(104)	(108)	1	0	0	-104	-104	20197	18909
07/27/23	2| 11| 1.5| 3| r2<80	48	666	658	2	690	1	-24	-24	20863	19567
07/28/23	2| 11| 1.5| 3| r2<80	55	270	266	1	270	1	0	0	21133	19833
07/31/23	2| 11| 1.5| 3| r2<80	65	0	0	0	0	0	0	0	21133	19833
08/01/23	2| 11| 1.5| 3| r2<80	65	0	0	0	0	0	0	0	21133	19833
08/02/23	2| 11| 1.5| 3| r2<80	65	358	354	1	358	1	0	0	21491	20187
08/03/23	2| 11| 1.5| 3| r2<80	71	0	0	0	0	0	0	0	21491	20187

Date	Inputs	IS R2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
08/04/23	2| 11| 1.5| 3| r2<80	68	(559)	(563)	1	0	0	-559	-559	20932	19624

Appendix I: n^{th} Order Polynomial Next Bar's Forecast Math

What is the n^{th} Order Polynomial ?

The n^{th} Order Polynomial, also called the n^{th} Order Fixed Memory Polynomial, is simply the least square fit of a polynomial of the form $\mathbf{b_0+b_1*t+b_2*t^2+b_3*t^3+\ldots b_n*t^n}$ to a ***fixed*** number of past data points. Where **t** is discrete time bars. Time could be daily bars or 5-minute bars. We use the term "Fixed Memory" to designate that only a fixed number of data points are used to calculate the polynomial coefficients. It is assumed that the time bars occur at fixed intervals of time so tic bars would not be appropriate for this analysis. Least squares is a mathematical technique where the squared vertical distance between the data and the curve that is being fit to the data is minimized. When the net squared distance (also called the sum of the squared errors) is minimized, a unique set of coefficients $\mathbf{b_0,b_1,b_2,\ldots,b_n}$ for the polynomial is determined. This type of error minimization is mathematically solvable and is widely used in science and mathematics.

For a 4^{th} order polynomial equation, the least squares coefficients are obtained from the solution of the following matrix equation.

$$\begin{vmatrix} T & \sum t & \sum t^2 & \sum t^3 & \sum t^4 \\ \sum t & \sum t^2 & \sum t^3 & \sum t^4 & \sum t^5 \\ \sum t^2 & \sum t^3 & \sum t^4 & \sum t^5 & \sum t^6 \\ \sum t^3 & \sum t^4 & \sum t^5 & \sum t^6 & \sum t^7 \\ \sum t^4 & \sum t^5 & \sum t^6 & \sum t^7 & \sum t^8 \end{vmatrix} \begin{vmatrix} a_0 \\ b_0 \\ c_0 \\ d_0 \\ e_0 \end{vmatrix} = \begin{vmatrix} \sum p(t) \\ \sum (p(t)*t) \\ \sum (p(t)*t^2) \\ \sum (p(t)*t^3) \\ \sum (p(t)*t^4) \end{vmatrix}$$

where

p(T) is the current bar's price, **p(T-1)** is the previous bar's price and **p(1)** is the price **T** bars ago.
T is the number of Bars in the Least Squares estimation
$\sum$**p(t)** is the summation of prices from **t=1 to T** bars
$\sum$**p(t)*t** is the summation of prices times t from **t=1 to T** bars
$\sum$**t** is the summation of the integer **t** from **t=1 to T** bars
$\sum \mathbf{t^2}$ is the summation of the integer **t** squared from **t=1 to T** bars
etc.

Once the coefficients to the polynomial have been solved for, we generate the forecast for the next bar's price which is given for the equation by:

$$\mathbf{P_f = a_0 + b_0*(T+1) + c_0*(T+1)^2 + d_0*(T+1)^3 + e_0*(T+1)^4}$$

Where $\mathbf{P_f}$ stands for price forecast.

With these coefficients, we can also generate the forecast for the next bar's ***velocity*** and ***velocity*** by the equations:

$$\mathbf{Velocity(T+1) = dP_f /dt = b_0 + 2c_0*(T+1) + 3d_0*(T+1)^2 + 4e_0*(T+1)^3}$$

$$\mathbf{Velocity(t+1) = d^2P_f /d^2t = 2\,c_0 + 6d_0*(T+1) + 12e_0*(T+1)^2}$$

We use the next bar forecast because changes in the trend are more quickly reflected in the forecast price, velocity and velocity than in the end point price, velocity and velocity.

Programs that solve for the solution to matrix equations can be found in the book "Numerical Recipes" by W. Press, et. al. However this type of matrix equation solvers are very slow and for these types of problems are unstable. They cause numerical errors and floating point overflows due to matrix inversion ill conditioning which produces false results.

Appendix I: n^{th} Order Polynomial Next Bar's Forecast Math

Fortunately, these types of problems can be solved by a fast, efficient and accurate algorithm using Discrete Orthogona1 Legendre Polynomials. This method is explained in detail in Norman Morrison' book entitled "Introduction to Sequential Smoothing and Prediction", Chapter 7 page 223., referenced at the end of this section.

Without going into detail here (see Morrison reference), the polynomial filter can now be represented by:

$$P_e(t) = \sum_{j=0}^{n} \beta_j * \phi_j(t) \quad j=0 \text{ to } n$$

Where **n** is the polynomial order, **T** is the total number of Bars of data used in the Least Squares fit and

$$\beta_j = \sum_{k=0}^{T-1} p(t-T+k) * \phi_j(k)$$

$\phi_j(t)$ = the *normalized* discrete Legendre polynomial. t = an integer from 0 to T

The coefficients, $\beta_0, \beta_1, \beta_2, \beta_3, , , , \beta_n$ for a **n^{th}** order polynomial can now be solved for by the equation above and we can generate the forecast for the next bar's close, velocity and velocity which are given by the equations

$$P_F(T+1) = \beta_0 * \phi_0(T+1) + \beta_1 * \phi_1(T+1) + \beta_2 * \phi_2(T+1) + \beta_3 * \phi_3(T+1) + \ldots + \beta_n * \phi_n(T+1)$$

$$\text{Velocity} = (dP_F/dt)_{(T+1)} = \beta_1 * (d\phi_1/dt)_{(T+1)} + \beta_2 * (d\phi_2/dt)_{(T+1)} + \beta_3 * (d\phi_3/dt)_{(T+1)} ++ \beta_n * (d\phi_n/dt)_{(T+1)}$$

$$\text{Velocity} = (d^2P_F/d^2t)_{(T+1)} = \beta_2 * (d^2\phi_2/d^2t)_{(T+1)} + \beta_3 * (d^2\phi_3/d^2t)_{(T+1)} + \ldots + \beta_n * (d^2\phi_n/d^2t)_{(T+1)}$$

The n^{th} Order Fixed Memory Forecast Next Bar's Velocity Strategy Defined

The least squares forecast is constructed by solving for the least squares coefficients $\beta_1, \beta_2, , , \beta_n$ at each bar using the last **T** bars of closing prices and the Discrete Orthogonal Legendre Polynomial equations for β_j above. Then **Velocity** = **$d^2P_F(T+1)/d^2t$** is constructed from the velocity equation above and plotted under the price chart. In general, what we will be doing is following the plotted curve of **Velocity** which is calculated at each bar from the previous T bars. When the velocity is greater than a threshold amount ***vup*** we will go long. When the velocity is less than a threshold amount ***-vdn*** we will go short.

Buy Rule:
IF Velocity is greater than the threshold amount ***vup*** then buy at the market.

Sell Rule:
IF Velocity is less than the threshold amount ***-vdn*** then sell at the market.

References

1. Morrison, Norman "Introduction to Sequential Smoothing and Prediction", McGraw-Hill Book Company, New York, 1969.

The *Normalization Multiplier*

What is the Multiplier?

The n^{th} Order Fixed Memory Polynomial, also called an n^{th} Order Polynomial, is the least square fit of a polynomial of the form $b_0+b_1*t+b_2*t^2+b_3*t^3+\ldots+b_n*t^n$ to a ***fixed*** number of past data points. Where **t** is discrete time bars. Time could be daily bars or 5-minute bars. We use the term "Fixed Memory" to designate that only a fixed number of data points are used to calculate the polynomial coefficients. It is assumed that the time bars occur at fixed intervals of time so tic bars would not be appropriate for this analysis. Least squares is a mathematical technique where the squared vertical distance between the data and the curve that is being fit to the data is minimized. When the net squared distance (also called the sum of the squared errors) is minimized, a unique set of coefficients $b_0,b_1,b_2,\ldots,b_n$ for the polynomial is determined. This type of error minimization is mathematically solvable and is widely used in science and mathematics. Once the b_n coefficients are found using a lookback period of **T** bars to calculate the b_n coefficients, then the next bar's estimate **(T+1)** of the n^{th} order polynomial velocity and acceleration can be easily found by the equations below.

Velocity(T+1) = $dP_f/dt = b_0 + 2c_0*(T+1) + 3d_0*(T+1)^2 + 4e_0*(T+1)^3 +\ldots.+n*b_n*(T+1)^{n-1}$

Acceleration(t+1) = $d^2P_f/d^2t = 2c_0 + 9d_0*(T+1) + 12e_0*(T+1)^3+\ldots\ldots.+ n*(n-1)*b_n*(T+1)^{n-2}$

Please see the ***n*th Order Fixed Memory Polynomial Next Bar's Forecast Math** section for a more detailed explanation.

For any tradable, the inputs to the polynomial are the **polynomial degree (Order)** and the number or lookback bars **N** (denoted by T in equations above). When we plot the velocity or acceleration, we notice that the amplitude, and the maximum and minimum values of the velocity or acceleration vary quite significantly with different degree and N inputs.

Below is a table of the standard deviation (SD) of the 56340 calculated Velocity values for different **degree** and **N** inputs. We used 1min bars of the E-Mini from 8/1/2014 to 2/20/2015 to generate this table. As one can see the standard deviation of the velocity for each degree and N vary greatly. For instance, for degree=4, N=20 the SD is 6.8 times the SD for degree=1, N=20. This creates problems when trying to determine the correct ranges for vup/vdn and aup/adn during optimization.

@ES.D 5 min bars Date Range 1140801 to 1150220
Total Number of Bars=56340 Norm=0
FixmVn Multiplier= 1/SD to Scale Velocity pw and N Range to One SD

Degree	N	SD	1/SD
1	20	0.1902	5.2565
1	30	0.1540	6.4916
1	40	0.1328	7.5279
1	50	0.1183	8.4502
1	60	0.1077	9.3810
1	70	0.0996	10.0440
avg		0.1338	7.8430
2	20	0.4351	2.2982
2	30	0.3443	2.9046
2	40	0.2936	3.4060
2	50	0.1583	3.8275
2	60	0.2371	4.2180
2	70	0.2173	4.6010

avg		**0.2981**	**3.5425**
3	**20**	**0.7854**	**1.2732**
3	**30**	**0.5933**	**1.6855**
3	**40**	**0.4973**	**2.0111**
3	**50**	**0.4347**	**2.3005**
3	**60**	**0.3949**	**2.5324**
3	**70**	**0.3656**	**2.7352**
avg		**0.5119**	**2.0897**
4	**20**	**1.2924**	**0.7738**
4	**30**	**0.9279**	**1.0777**
4	**40**	**0.7582**	**1.3189**
4	**5**	**0.6542**	**1.5285**
4	**60**	**0.5804**	**1.7228**
4	**70**	**0.5314**	**1.8818**
avg		**0.7908**	**1.3839**

The problem may get worse when we want to find good inputs for other tradables. Other tradables, because of their scales and tick size have much different Velocity ranges then the E-Mini for the same degree and N. Thus, the NS search ranges have to be different for each different tradable.

To solve this problem and to have a standard search space for each tradable, I created a **Mult** input for each FixmXVA Velocity and Acceleration strategy and indicator. If each tradable's Velocity is multiplied by a number such that the standard deviation of that tradable's Velocity is around one, then the search space for vup and vdn for each tradable would be 0 to 3.5 SDs and we wouldn't have to change the TS search space every time we wanted to examine a new stock or future. The complicated equations that I use to normalize the ranges to one standard deviation were derived using the software TableCurve 3D, automated surface and equation discovery.