Trading QQQ ETF 5min Bars Using the nth Order Fixed Memory Polynomial Velocity Algorithm
Walk Forward in-sample 10 Trading weekdays and out-of-sample 1 Trading weekday.
1/4/2022 to 10/27/2023 using The Walk Forward Input Explorer
Working Paper November 2023 Copyright © 2023 Dennis Meyers

Disclaimer

The strategies, methods and indicators presented here are given for educational purposes only and should not be construed as investment advice. Be aware that the profitable performance presented here is based upon hypothetical trading with the benefit of hindsight and can in no way be assumed nor can it be claimed that the strategy and methods presented here will be profitable in the future or that they will not result in losses.

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 1/4/2022 to 10/27/2023.

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 2nd 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 Invesco QQQ Trust Series ETF traded on the NYSE and known by the symbol QQQ for the 449 trading days from January 4, 2022, to October 27, 2023. However, The Walk Forward Input Explorer will only analyses data from 1/4/2022 to 8/4/2023. 8/7/23 to 10/27/23 will be withheld to see how the filter applied to the 1/4/2022-8/4/2023 data did in the next 60 weekdays days of 8/7/23 to 10/27/23.

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 10 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. 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 **389, 10 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 9-day ***IS***. All other ***IS*** periods consist of 10 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 389 in-sample/out-of-sample files for the 20 months of 5 min bar QQQ data.

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

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 10 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-filter*** we will use here: in-sample Profit Factor (**PF**≤ **x**) and/or Losers in a row (**lr** ≤ **y)**, and/or equity curve straight line correlation coefficient (**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 inputs 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 389 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 389 days from 01/04/2022 to 8/4/2023. The in-sample (IS) period is 10 trading weekdays, and the out-of-sample (OOS) period is 1 trading weekday. This strategy traded between 9am to 1555pm Exchange Time (EST). The next section on each input line is how the ***Filter*** did on the next 60 days from 8/7/2023 to 10/27/2023. This section of data was not involved in the Walk Forward Input Explorer filter selection from 1/4/2022 to 8/4/2023.

From this run, we chose the filter on row 3 of the Figure below. That is,
----

3|14|1.25|1.5|0|1555|13.8|pf<5|lr<5. This is constructed as follows.
For the strategy inputs **3|14|1.25|1.5|0|1555|13.8** only those in-sample sections that have a **pf ≤5 and LR<5** are used to trade in the following out-of-sample next trading day section. If the in-sample pf > 5 or LR>5, then the next trading day out-of-sample section ***is not*** traded.

<table>
<tr><td>QQQ5mFixmV10x1dxoa</td><td>s01/18/22</td><td>e08/04/23</td><td>#389</td><td>AnyTnp</td><td>#60</td><td></td><td></td><td></td><td></td><td>ISnt2</td><td></td><td></td><td>a3.0</td><td>s17.5</td><td>f564479</td><td></td><td></td><td></td><td></td><td>c=$4</td><td></td><td></td><td></td><td></td></tr>
<tr><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></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|pf<5|lr<5</td><td>28994</td><td>26070</td><td>107</td><td>39.7</td><td>2.7</td><td>270</td><td>395</td><td>0.056</td><td>4.43</td><td>4.47</td><td>1.38</td><td>53</td><td>62</td><td>-659</td><td>-1126</td><td>-2571</td><td>12</td><td>5</td><td>49</td><td>92</td><td>95</td><td>69</td><td>82</td><td>690</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|lr<5</td><td>28853</td><td>25825</td><td>103</td><td>38.1</td><td>2.7</td><td>279</td><td>393</td><td>0.083</td><td>4.4</td><td>4.4</td><td>1.38</td><td>52</td><td>61</td><td>-659</td><td>-1126</td><td>-2571</td><td>9</td><td>5</td><td>43</td><td>92</td><td>94</td><td>69</td><td>84</td><td>654</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|pf<4|lr<5</td><td>27340</td><td>24568</td><td>107</td><td>39.5</td><td>2.7</td><td>256</td><td>398</td><td>0.063</td><td>4.47</td><td>4.29</td><td>1.39</td><td>52</td><td>62</td><td>-659</td><td>-1126</td><td>-2119</td><td>13</td><td>3</td><td>47</td><td>92</td><td>94</td><td>68</td><td>89</td><td>617</td></tr>
<tr><td>1|8|1|1|0|1555|13.8|pf<3|lr<5</td><td>26055</td><td>23543</td><td>93</td><td>41.5</td><td>2.2</td><td>280</td><td>379</td><td>-0.128</td><td>3.26</td><td>4.11</td><td>1.66</td><td>47</td><td>60</td><td>-712</td><td>-1107</td><td>-2447</td><td>9</td><td>5</td><td>20</td><td>89</td><td>93</td><td>52</td><td>97</td><td>679</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|pf<3|</td><td>26831</td><td>23335</td><td>77</td><td>30.7</td><td>2.5</td><td>347</td><td>417</td><td>0.001</td><td>3.88</td><td>3.45</td><td>1.67</td><td>45</td><td>61</td><td>-565</td><td>-1315</td><td>-4314</td><td>8</td><td>5</td><td>11</td><td>86</td><td>90</td><td>81</td><td>137</td><td>239</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3r2<80</td><td>24412</td><td>23268</td><td>140</td><td>85.4</td><td>1.6</td><td>174</td><td>425</td><td>0.181</td><td>3.71</td><td>4.35</td><td>1.75</td><td>52</td><td>61</td><td>-821</td><td>-1128</td><td>-2234</td><td>6</td><td>5</td><td>25</td><td>89</td><td>87</td><td>91</td><td>86</td><td>431</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|</td><td>27047</td><td>23259</td><td>72</td><td>28.6</td><td>2.5</td><td>376</td><td>413</td><td>0</td><td>3.83</td><td>3.38</td><td>1.66</td><td>45</td><td>60</td><td>-565</td><td>-1315</td><td>-4314</td><td>8</td><td>5</td><td>11</td><td>86</td><td>89</td><td>92</td><td>143</td><td>196</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|pf<4|</td><td>26410</td><td>22742</td><td>73</td><td>28.8</td><td>2.5</td><td>364</td><td>414</td><td>0.006</td><td>3.88</td><td>3.34</td><td>1.67</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>89</td><td>92</td><td>146</td><td>188</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|pf<5|</td><td>26190</td><td>22470</td><td>71</td><td>28.2</td><td>2.5</td><td>369</td><td>413</td><td>0.008</td><td>3.86</td><td>3.3</td><td>1.66</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>89</td><td>92</td><td>150</td><td>181</td></tr>
<tr><td>2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5r2<80</td><td>24746</td><td>22398</td><td>101</td><td>42.2</td><td>2.4</td><td>246</td><td>424</td><td>0.469</td><td>5.43</td><td>3.72</td><td>1.42</td><td>52</td><td>61</td><td>-955</td><td>-1171</td><td>-3184</td><td>11</td><td>5</td><td>88</td><td>89</td><td>96</td><td>72</td><td>118</td><td>377</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3</td><td>23455</td><td>22231</td><td>129</td><td>76.7</td><td>1.7</td><td>182</td><td>434</td><td>0.087</td><td>3.71</td><td>4.01</td><td>1.71</td><td>51</td><td>61</td><td>-1095</td><td>-1128</td><td>-2234</td><td>6</td><td>5</td><td>25</td><td>88</td><td>86</td><td>91</td><td>102</td><td>328</td></tr>
<tr><td>1|7|1.75|1.25|0|1555|13.8|pf<2|lr<5r2<60</td><td>23478</td><td>22126</td><td>108</td><td>69.5</td><td>1.6</td><td>217</td><td>376</td><td>0.16</td><td>3.52</td><td>4.24</td><td>1.5</td><td>53</td><td>64</td><td>-712</td><td>-856</td><td>-1379</td><td>7</td><td>4</td><td>20</td><td>94</td><td>94</td><td>28</td><td>91</td><td>1466</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|lr<3r2<80</td><td>23194</td><td>21954</td><td>122</td><td>74.8</td><td>1.6</td><td>190</td><td>420</td><td>0.247</td><td>3.65</td><td>4</td><td>1.73</td><td>50</td><td>59</td><td>-821</td><td>-1128</td><td>-2234</td><td>5</td><td>5</td><td>25</td><td>91</td><td>86</td><td>58</td><td>102</td><td>531</td></tr>
<tr><td>2|9|1.5|1.75|0|1555|13.8|pf<3|</td><td>24640</td><td>21828</td><td>84</td><td>35</td><td>2.4</td><td>295</td><td>425</td><td>0.212</td><td>3.91</td><td>3.38</td><td>1.49</td><td>48</td><td>60</td><td>-688</td><td>-1368</td><td>-2474</td><td>7</td><td>5</td><td>42</td><td>89</td><td>94</td><td>63</td><td>143</td><td>314</td></tr>
<tr><td>3|14|1.75|1.5|0|1555|13.8|lr<5</td><td>24243</td><td>21767</td><td>93</td><td>39.2</td><td>2.4</td><td>260</td><td>399</td><td>-0.009</td><td>3.46</td><td>3.77</td><td>1.4</td><td>51</td><td>58</td><td>-689</td><td>-1233</td><td>-2981</td><td>11</td><td>6</td><td>3</td><td>60</td><td>76</td><td>132</td><td>115</td><td>113</td></tr>
<tr><td>2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5</td><td>24140</td><td>21752</td><td>97</td><td>40.4</td><td>2.4</td><td>250</td><td>422</td><td>0.492</td><td>5.47</td><td>3.62</td><td>1.43</td><td>52</td><td>60</td><td>-955</td><td>-1171</td><td>-3184</td><td>11</td><td>5</td><td>88</td><td>89</td><td>96</td><td>73</td><td>125</td><td>340</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|pf<4|lr<3r2<80</td><td>22927</td><td>21727</td><td>125</td><td>76.4</td><td>1.6</td><td>183</td><td>423</td><td>0.237</td><td>3.68</td><td>4.01</td><td>1.72</td><td>51</td><td>60</td><td>-821</td><td>-1128</td><td>-2234</td><td>5</td><td>5</td><td>23</td><td>88</td><td>85</td><td>92</td><td>102</td><td>320</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|pf<3|lr<5</td><td>24290</td><td>21714</td><td>103</td><td>37.7</td><td>2.7</td><td>235</td><td>389</td><td>0.173</td><td>4.69</td><td>4.08</td><td>1.41</td><td>52</td><td>61</td><td>-659</td><td>-1126</td><td>-2119</td><td>10</td><td>3</td><td>47</td><td>92</td><td>94</td><td>71</td><td>98</td><td>510</td></tr>
</table>

<table>
<tr><td>QQQ5mFixmV10x1dxoa</td><td>|</td><td>s08/07/23</td><td>e10/27/23</td><td>#60</td><td></td><td></td><td></td><td>t449</td></tr>
<tr><td>pw|N|vup|vdn|xop|xt|mult|<PF<LR<R2</td><td>|</td><td>toGPx</td><td>toNPx</td><td>aoTRx</td><td>aoNTx</td><td>#x</td><td>tOnpNet</td><td>Prob</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|pf<5|lr<5</td><td>|</td><td>3563</td><td>3279</td><td>50</td><td>2</td><td>35</td><td>29349</td><td>4.552e-8</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|lr<5</td><td>|</td><td>4503</td><td>4163</td><td>53</td><td>1.9</td><td>44</td><td>29988</td><td>1.562e-7</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|pf<4|lr<5</td><td>|</td><td>3474</td><td>3194</td><td>50</td><td>2.1</td><td>34</td><td>27762</td><td>5.474e-8</td></tr>
<tr><td>1|8|1|1|0|1555|13.8|pf<3|lr<5</td><td>|</td><td>3447</td><td>3027</td><td>33</td><td>1.9</td><td>56</td><td>26570</td><td>1.815e-6</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|pf<3|</td><td>|</td><td>2110</td><td>1654</td><td>19</td><td>2</td><td>56</td><td>24989</td><td>1.211e-4</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3r2<80</td><td>|</td><td>651</td><td>555</td><td>27</td><td>1.2</td><td>20</td><td>23823</td><td>4.147e-14</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|</td><td>|</td><td>2110</td><td>1654</td><td>19</td><td>2</td><td>56</td><td>24913</td><td>3.859e-4</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|pf<4|</td><td>|</td><td>2110</td><td>1654</td><td>19</td><td>2</td><td>56</td><td>24396</td><td>3.393e-4</td></tr>
<tr><td>1|7|1|1|0|1555|13.8|pf<5|</td><td>|</td><td>2110</td><td>1654</td><td>19</td><td>2</td><td>56</td><td>24124</td><td>4.704e-4</td></tr>
<tr><td>2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5r2<80</td><td>|</td><td>189</td><td>(135)</td><td>2</td><td>1.7</td><td>48</td><td>22263</td><td>2.461e-7</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3</td><td>|</td><td>651</td><td>555</td><td>27</td><td>1.2</td><td>20</td><td>22786</td><td>5.053e-12</td></tr>
<tr><td>1|7|1.75|1.25|0|1555|13.8|pf<2|lr<5r2<60</td><td>|</td><td>3526</td><td>3390</td><td>104</td><td>1.2</td><td>28</td><td>25516</td><td>7.907e-9</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|lr<3r2<80</td><td>|</td><td>699</td><td>571</td><td>22</td><td>1.2</td><td>26</td><td>22525</td><td>6.461e-11</td></tr>
<tr><td>2|9|1.5|1.75|0|1555|13.8|pf<3|</td><td>|</td><td>108</td><td>(176)</td><td>2</td><td>1.7</td><td>41</td><td>21652</td><td>2.501e-5</td></tr>
<tr><td>3|14|1.75|1.5|0|1555|13.8|lr<5</td><td>|</td><td>2936</td><td>2692</td><td>48</td><td>1.6</td><td>39</td><td>24459</td><td>2.005e-6</td></tr>
<tr><td>2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5</td><td>|</td><td>189</td><td>(135)</td><td>2</td><td>1.7</td><td>48</td><td>21617</td><td>7.988e-7</td></tr>
<tr><td>2|11|1.5|2.5|0|1555|13.8|pf<4|lr<3r2<80</td><td>|</td><td>153</td><td>53</td><td>6</td><td>1.2</td><td>21</td><td>21780</td><td>1.927e-11</td></tr>
<tr><td>3|14|1.25|1.5|0|1555|13.8|pf<3|lr<5</td><td>|</td><td>3137</td><td>2893</td><td>51</td><td>2.2</td><td>28</td><td>24607</td><td>1.641e-7</td></tr>
</table>

This is the 2nd section from 08/7/2023 to 10/27/2023 which was not included in the Walk Forward Input Explorer(WFINP) run. This is how the filter found by the WFINP on the 1/4/2023-8/4/2023 data performed on the next 60 trading days. As one can see many of the filters found performed well on data that they had not been developed on.

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 389 out-of-sample files of **$3.0** with a bootstrap standard deviation of **$17.5**. (Side Note. The average is the average per out-of-sample period. So, the average for the random selection would be the random toNP/389 and the average for the filter would be the filter toNP/# of OOS periods traded or 26070/270=96.5). The probability of obtaining our filters average daily net profit **of 96.5** is **4.552×10^{-8}** which is **5.3** standard deviations from the bootstrap average. For our filter, in row 3 above, the expected number of cases that we could obtain by pure chance that would match or exceed **$96.5** is $[1-(1-\mathbf{4.552 \times 10^{-8}})^{564479}$**] ~ 564479*4.552x10^{-8}** = **0.0257** where **564479** is the total number of different filters we looked at in this run. This number is much less than one, so it is improbable 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 389 days from 1/4/22 to 8/4/23. Separated by a red line from the data from 60 trading days from 8/7/23 to 10/17/23 that were not included in the WFINP filter search. 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 10/4/2023-10/17/2023.

Table 1 below presents a table of the 389 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. Plus, the 60 trading days from 8/7/23 to 10/27/23 that were not included in the WFINP filter that was run from 1/4/23 – 8/7/23.

Discussion of Strategy Performance

In Figure 3, Row 4 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 **69** days for this filter. This means that 69 trading days, a little over two months, 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=62%**. The average oos winning trade to the average oos losing trade ratio(**oW|oL**) was **1.38**. **wpr=12** 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 ($659) and the largest losing day was ($1126). The average trade was $39.7 for the 1/18/23-8/4/23 period and $50 for the 8/7/23-10/27/23 period.

In Figure 1, which presents a graph of the equity curve using the filter on the 389 trading days of out-of-sample data, notice how the equity curve follows the 2nd order polynomial trend line with an R^2 of 0.965. The R^2 only dropped to 0.959 for the net equity curve.

Using this filter, the strategy was able to generate $26070 net equity after commissions of $0 (many brokers today, 11/01/23, don't charge commissions) and roundtrip slippage of $4 trading 100 QQQ ETF shares for 389 days. The filter generated an extra $3279 net equity between 8/4/23 to 10/27/23 the data that was not included in the WFINP filter run for a total of $29,349 net equity. This period from 1/18/22 to 10/27/23 was a volatile down then up market as can be seen from the QQQ close on the chart. 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 9 trades/day with an average of 2.7 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 270 days out of the 389 days or 69% of the time. For the 8/7/23-10/27/23 period the **input|filter** traded 35 days out of 60 or 58% of the time.

If a 2.7 trades per day is too much row 13, 1|7|1.75|1.25|0 |1555|13.8|pf<2|lr<5r2<60 while offering less profit only trades an average of 1.5 trades per day and trades only 55% 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 01/02/2022 to 7/9/2020

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.

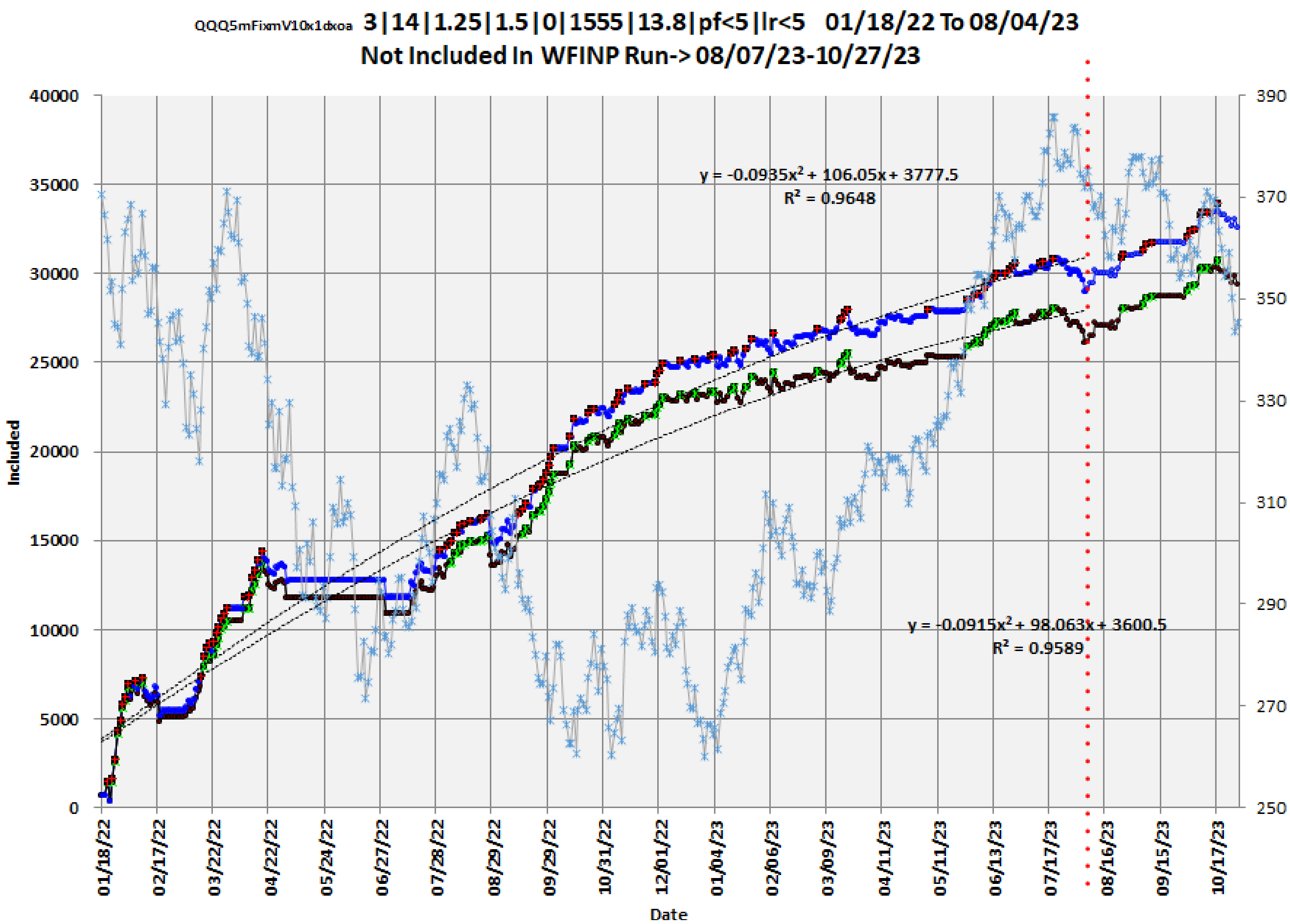

Figure 2 Walk Forward Out-Of-Sample Performance Summary for nth Order Fixed Memory Polynomial Velocity Strategy QQQ 5-minute bar chart from 6/22/23 to 6/30/23.

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

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
1	QQQ5mFixmV10x1dxoa	s01/18/22	e08/04/23	#389	AnyTnp	#60					ISnt2			a3.0	s17.5	f564479					c=$4				
2	pw|N|vup|vdn|xop|xt|mult|<PF<LR<R2	toGP	tONP	aoGP	aoTr	ao#T	#	std	skew	kur	t	oW|oL	%Wtr	%P	LLtr	LLp	eqDD	wpr	lpr	V20	KTau	eqR2	Blw	BE	tkr|bl
3	3|14|1.25|1.5|0|1555|13.8|pf<5|lr<5	28994	26070	107	39.7	2.7	270	395	0.056	4.43	4.47	1.38	53	62	-659	-1126	-2571	12	5	49	92	95	69	82	690
4	3|14|1.25|1.5|0|1555|13.8|lr<5	28853	25825	103	38.1	2.7	279	393	0.083	4.4	4.4	1.38	52	61	-659	-1126	-2571	9	5	43	92	94	69	84	654
5	3|14|1.25|1.5|0|1555|13.8|pf<4|lr<5	27340	24568	107	39.5	2.7	256	398	0.063	4.47	4.29	1.39	52	62	-659	-1126	-2119	13	3	47	92	94	68	89	617
6	1|8|1|1|0|1555|13.8|pf<3|lr<5	26055	23543	93	41.5	2.2	280	379	-0.128	3.26	4.11	1.66	47	60	-712	-1107	-2447	9	5	20	89	93	52	97	679
7	1|7|1|1|0|1555|13.8|pf<3|	26831	23335	77	30.7	2.5	347	417	0.001	3.88	3.45	1.67	45	61	-565	-1315	-4314	8	5	11	86	90	81	137	239
8	2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3r2<80	24412	23268	140	85.4	1.6	174	425	0.181	3.71	4.35	1.75	52	61	-821	-1128	-2234	6	5	25	89	87	91	86	431
9	1|7|1|1|0|1555|13.8|	27047	23259	72	28.6	2.5	376	413	0	3.83	3.38	1.66	45	60	-565	-1315	-4314	8	5	11	86	89	92	143	196
10	1|7|1|1|0|1555|13.8|pf<4|	26410	22742	73	28.8	2.5	364	414	0.006	3.88	3.34	1.67	44	60	-565	-1315	-4314	8	5	11	85	89	92	146	188
11	1|7|1|1|0|1555|13.8|pf<5|	26190	22470	71	28.2	2.5	369	413	0.008	3.86	3.3	1.66	44	60	-565	-1315	-4314	8	5	11	85	89	92	150	181
12	2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5r2<80	24746	22398	101	42.2	2.4	246	424	0.469	5.43	3.72	1.42	52	61	-955	-1171	-3184	11	5	88	89	96	72	118	377
13	2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3	23455	22231	129	76.7	1.7	182	434	0.087	3.71	4.01	1.71	51	61	-1095	-1128	-2234	6	5	25	88	86	91	102	328
14	1|7|1.75|1.25|0|1555|13.8|pf<2|lr<5r2<60	23478	22126	108	69.5	1.6	217	376	0.16	3.52	4.24	1.5	53	64	-712	-856	-1379	7	4	20	94	94	28	91	1466
15	2|11|1.5|2.5|0|1555|13.8|lr<3r2<80	23194	21954	122	74.8	1.6	190	420	0.247	3.65	4	1.73	50	59	-821	-1128	-2234	5	5	25	91	86	58	102	531
16	2|9|1.5|1.75|0|1555|13.8|pf<3|	24640	21828	84	35	2.4	295	425	0.212	3.91	3.38	1.49	48	60	-688	-1368	-2474	7	5	42	89	94	63	143	314
17	3|14|1.75|1.5|0|1555|13.8|lr<5	24243	21767	93	39.2	2.4	260	399	-0.009	3.46	3.77	1.4	51	58	-689	-1233	-2981	11	6	3	60	76	132	115	113
18	2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5	24140	21752	97	40.4	2.4	250	422	0.492	5.47	3.62	1.43	52	60	-955	-1171	-3184	11	5	88	89	96	73	125	340
19	2|11|1.5|2.5|0|1555|13.8|pf<4|lr<3r2<80	22927	21727	125	76.4	1.6	183	423	0.237	3.68	4.01	1.72	51	60	-821	-1128	-2234	5	5	23	88	85	92	102	320
20	3|14|1.25|1.5|0|1555|13.8|pf<3|lr<5	24290	21714	103	37.7	2.7	235	389	0.173	4.69	4.08	1.41	52	61	-659	-1126	-2119	10	3	47	92	94	71	98	510

	A	AA	AB	AC	AD	AE	AF	AG
1	QQQ5mFixmV10x1dxoa		s08/07/23	e10/27/23	#60			t449
2	pw|N|vup|vdn|xop|xt|mult|<PF<LR<R2	Prob	toGPx	toNPx	aoTRx	aoNTx	#x	tOnpNet
3	3|14|1.25|1.5|0|1555|13.8|pf<5|lr<5	4.552e-8	3563	3279	50	2	35	29349
4	3|14|1.25|1.5|0|1555|13.8|lr<5	1.562e-7	4503	4163	53	1.9	44	29988
5	3|14|1.25|1.5|0|1555|13.8|pf<4|lr<5	5.474e-8	3474	3194	50	2.1	34	27762
6	1|8|1|1|0|1555|13.8|pf<3|lr<5	1.815e-6	3447	3027	33	1.9	56	26570
7	1|7|1|1|0|1555|13.8|pf<3|	1.211e-4	2110	1654	19	2	56	24989
8	2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3r2<80	4.147e-14	651	555	27	1.2	20	23823
9	1|7|1|1|0|1555|13.8|	3.859e-4	2110	1654	19	2	56	24913
10	1|7|1|1|0|1555|13.8|pf<4|	3.393e-4	2110	1654	19	2	56	24396
11	1|7|1|1|0|1555|13.8|pf<5|	4.704e-4	2110	1654	19	2	56	24124
12	2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5r2<80	2.461e-7	189	(135)	2	1.7	48	22263
13	2|11|1.5|2.5|0|1555|13.8|pf<3|lr<3	5.053e-12	651	555	27	1.2	20	22786
14	1|7|1.75|1.25|0|1555|13.8|pf<2|lr<5r2<60	7.907e-9	3526	3390	104	1.2	28	25516
15	2|11|1.5|2.5|0|1555|13.8|lr<3r2<80	6.461e-11	699	571	22	1.2	26	22525
16	2|9|1.5|1.75|0|1555|13.8|pf<3|	2.501e-5	108	(176)	2	1.7	41	21652
17	3|14|1.75|1.5|0|1555|13.8|lr<5	2.005e-6	2936	2692	48	1.6	39	24459
18	2|10|0.5|1.75|0|1555|13.8|pf<2|lr<5	7.988e-7	189	(135)	2	1.7	48	21617
19	2|11|1.5|2.5|0|1555|13.8|pf<4|lr<3r2<80	1.927e-11	153	53	6	1.2	21	21780
20	3|14|1.25|1.5|0|1555|13.8|pf<3|lr<5	1.641e-7	3137	2893	51	2.2	28	24607

The WFINP AVE File Output Cols are defined as follows.

Row 1 QQQ5Fixm10x1dxoa is the PWFO output files abbreviation, First OOS Day End Date (1/18/22), Last OOS Day End Date (8/4/23), **Number of days** (#389) 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).

Row 2 to Last Row Columns: A through Z

Col A: ***The Strategy Input/Filter Names***
Row 3: **3|14|1.25|1.5|0|1555|13.8|pf<5|LR<5 :** The inputs **3|14|1.25|1.5|0|1555|13.8|**for all in-sample files that have **PF≤5 and LR≤5**.
Col B: ***toGP*** Total out-of-sample(oos) gross profit for these 389 oos periods (for this run periods = weeks).
Col C: ***toNP*** Total out-of-sample(oos) Net profit (toGP-(# of Trade days)*cost) for the 389 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: ***#*** The number of oos periods this filter produced any profit or loss. Note for some oos periods there are no trades.
Col H: ***std*** the standard deviation of the # oos period profits and losses
Col I: ***skew*** The Skew statistic of the # oos period profits and losses.
Col J: ***kur*** the kurtosis statistic of the # oos period profits and losses
Col K: ***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 L: ***oW|oL*** Ratio of average oos winning trades divided by average oos losing trades.
Col M: ***%Wtr*** The percentage if oos winning trades.
Col N: ***%P*** percent of all oos periods that were profitable.
Col O ***LLtr*** the largest losing oos trade in all oos periods
Col P: ***LLp*** the largest losing oos period
Col Q: ***eqDD*** the oos equity drawdown
Col R: ***wpr*** the largest number of winning oos periods (weeks) in a row.
Col S: ***lpr*** the largest number of losing oos periods in a row.
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: ***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 V: ***eqR2*** the correlation coefficient(R^2) of a straight line fit to the equity curve.
Col W: ***Blw*** The maximum number of oos periods the oos equity curve failed to make a new high.
Col X: ***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 Y: ***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.

The Following columns are the results from 8/7/23-10/27/23 that were not included in the filter scan from 1/18/23 to 8/4/23.

Col AB: ***toGPx*** Total gross profit for the 52 future excluded periods (for this run periods = weeks).
Col AC: ***toNPx*** Total Net profit {toGP-Number of Trade Weeks(#)*cost} for the 52 future excluded periods.
Col AD: ***aoTrx*** Average profit per trade for the 52 future excluded periods
Col AE: ***aoNTx*** Average number of trades per week for the 52 future excluded periods
Col AF: ***#x*** the number of the 52 future excluded periods this strategy/filter traded. Note for some periods there can be no strategy inputs/filter that satisfy the Strategy Inputs/Filter criteria and no trades will be made during that period.
Col AG: ***tOnpNet -*** toNP+toNPx = Total Net Profits of oos+future periods

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

QQQ-5 min bars 01/18/2022 - 10/27/2023.

Filter: **3|14|1.25|1.5|0|1555|13.8|pf<5|lr<5;** The inputs **3|14|1.25|1.5|0|1555|13.8** for all in-sample files that have **PF≤5 and lr≤5**.
are used to trade in the following out-of-sample sections.

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	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
1/18/2022	1.86	3	710	698	3	804	2	-94	-94	710	698
1/19/2022	2.35	3	-6	-18	3	318	2	-324	-324	704	680
1/20/2022	2.02	3	813	797	4	1102	2	-220	-289	1517	1477
1/21/2022	2.65	3	-1126	-1150	6	117	2	-659	-1126	391	327
1/24/2022	1.57	3	1229	1201	7	1748	4	-388	-394	1620	1528
1/25/2022	1.58	3	1096	1076	5	1140	4	-44	-44	2716	2604
1/26/2022	1.95	3	1622	1602	5	1622	5	0	0	4338	4206
1/27/2022	2.66	2	567	531	9	1047	4	-257	-480	4905	4737
1/28/2022	2.53	5	918	894	6	1281	5	-363	-363	5823	5631
1/31/2022	2.74	5	414	410	1	414	1	0	0	6237	6041
2/1/2022	2.86	5	733	725	2	733	2	0	0	6970	6766
2/2/2022	2.92	5	-683	-695	3	58	1	-403	-741	6287	6071
2/3/2022	2.52	5	520	500	5	771	2	-228	-250	6807	6571
2/4/2022	2.45	5	350	338	3	370	2	-20	-20	7157	6909
2/7/2022	3.8	5	-483	-499	4	174	1	-407	-657	6674	6410
2/8/2022	2.98	5	465	461	1	465	1	0	0	7139	6871
2/9/2022	2.76	5	189	177	3	310	1	-68	-121	7328	7048
2/10/2022	2.14	5	-792	-828	9	360	3	-295	-986	6536	6220
2/11/2022	1.49	4	-248	-268	5	538	1	-245	-541	6288	5952
2/14/2022	1.12	4	-188	-200	3	284	1	-468	-472	6100	5752
2/15/2022	0.97	4	192	180	3	235	1	-26	-43	6292	5932
2/16/2022	0.84	4	480	472	2	480	2	0	0	6772	6404
2/17/2022	1.14	4	-464	-472	2	144	1	-608	-608	6308	5932
2/18/2022	0.87	4	-1099	-1127	7	165	1	-328	-1099	5209	4805
2/22/2022	0.67	5	263	243	5	988	3	-459	-725	5472	5048
2/23/2022	0.68	7	0	0	0	0	0	0	0	5472	5048

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
2/24/2022	0.57	7	0	0	0	0	0	0	0	5472	5048
2/25/2022	0.64	7	0	0	0	0	0	0	0	5472	5048
2/28/2022	0.71	7	0	0	0	0	0	0	0	5472	5048
3/1/2022	0.67	7	0	0	0	0	0	0	0	5472	5048
3/2/2022	0.62	7	0	0	0	0	0	0	0	5472	5048
3/3/2022	0.47	7	0	0	0	0	0	0	0	5472	5048
3/4/2022	0.51	7	0	0	0	0	0	0	0	5472	5048
3/7/2022	0.54	5	167	159	2	588	1	-421	-421	5639	5207
3/8/2022	0.6	5	385	349	9	1412	4	-357	-869	6024	5556
3/9/2022	0.63	5	-154	-174	5	145	2	-147	-179	5870	5382
3/10/2022	0.68	5	210	194	4	474	2	-149	-264	6080	5576
3/11/2022	0.73	5	563	559	1	563	1	0	0	6643	6135
3/14/2022	0.76	5	447	439	2	566	1	-119	-119	7090	6574
3/15/2022	0.96	5	279	259	5	608	2	-128	-329	7369	6833
3/16/2022	1.12	5	1171	1151	5	1468	3	-263	-297	8540	7984
3/17/2022	1.8	5	451	439	3	555	2	-104	-104	8991	8423
3/18/2022	1.88	5	283	267	4	614	3	-331	-331	9274	8690
3/21/2022	2.19	5	-478	-506	7	139	1	-183	-478	8796	8184
3/22/2022	1.93	4	539	535	1	539	1	0	0	9335	8719
3/23/2022	2.4	4	461	449	3	461	3	0	0	9796	9168
3/24/2022	2.9	4	393	385	2	541	1	-148	-148	10189	9553
3/25/2022	3.11	4	496	488	2	496	2	0	0	10685	10041
3/28/2022	3.08	4	202	194	2	243	1	-41	-41	10887	10235
3/29/2022	3.03	4	291	279	3	424	2	-133	-133	11178	10514
3/30/2022	3.28	4	0	0	0	0	0	0	0	11178	10514
3/31/2022	2.92	4	0	0	0	0	0	0	0	11178	10514
4/1/2022	2.72	4	0	0	0	0	0	0	0	11178	10514
4/4/2022	3.03	4	0	0	0	0	0	0	0	11178	10514
4/5/2022	8.4	1	0	0	0	0	0	0	0	11178	10514
4/6/2022	6.72	1	0	0	0	0	0	0	0	11178	10514
4/7/2022	2.47	4	704	692	3	704	3	0	0	11882	11206
4/8/2022	3.26	4	10	2	2	119	1	-109	-109	11892	11208
4/11/2022	2.32	4	47	35	3	228	1	-144	-181	11939	11243
4/12/2022	1.95	4	984	972	3	984	3	0	0	12923	12215
4/13/2022	2.99	4	437	433	1	437	1	0	0	13360	12648
4/14/2022	3.54	4	563	559	1	563	1	0	0	13923	13207
4/18/2022	4.26	4	-217	-221	1	0	0	-217	-217	13706	12986
4/19/2022	3.34	4	733	729	1	733	1	0	0	14439	13715
4/20/2022	4.07	4	-407	-423	4	13	1	-175	-420	14032	13292
4/21/2022	4.08	3	-191	-219	7	532	3	-288	-313	13841	13073
4/22/2022	2.19	4	-535	-559	6	283	2	-359	-710	13306	12514
4/25/2022	1.6	4	-110	-138	7	438	4	-207	-410	13196	12376
4/26/2022	1.46	4	-63	-75	3	385	2	-448	-448	13133	12301
4/27/2022	1.07	4	373	341	8	1133	4	-237	-523	13506	12642

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
4/28/2022	1.04	4	107	79	7	897	3	-308	-790	13613	12721
4/29/2022	0.93	4	86	66	5	867	2	-369	-631	13699	12787
5/2/2022	0.96	4	-163	-187	6	832	2	-397	-995	13536	12600
5/3/2022	0.97	4	-812	-832	5	0	0	-266	-812	12724	11768
5/4/2022	0.76	5	58	42	4	673	2	-381	-381	12782	11810
5/5/2022	0.83	6	0	0	0	0	0	0	0	12782	11810
5/6/2022	0.75	8	0	0	0	0	0	0	0	12782	11810
5/9/2022	0.8	8	0	0	0	0	0	0	0	12782	11810
5/10/2022	0.81	8	0	0	0	0	0	0	0	12782	11810
5/11/2022	0.87	8	0	0	0	0	0	0	0	12782	11810
5/12/2022	0.64	10	0	0	0	0	0	0	0	12782	11810
5/13/2022	0.69	10	0	0	0	0	0	0	0	12782	11810
5/16/2022	0.74	10	0	0	0	0	0	0	0	12782	11810
5/17/2022	0.74	10	0	0	0	0	0	0	0	12782	11810
5/18/2022	0.83	10	0	0	0	0	0	0	0	12782	11810
5/19/2022	0.86	10	0	0	0	0	0	0	0	12782	11810
5/20/2022	0.81	10	0	0	0	0	0	0	0	12782	11810
5/23/2022	0.81	10	0	0	0	0	0	0	0	12782	11810
5/24/2022	0.78	10	0	0	0	0	0	0	0	12782	11810
5/25/2022	0.78	8	0	0	0	0	0	0	0	12782	11810
5/26/2022	1.09	6	0	0	0	0	0	0	0	12782	11810
5/27/2022	1.14	6	0	0	0	0	0	0	0	12782	11810
5/31/2022	1.06	6	0	0	0	0	0	0	0	12782	11810
6/1/2022	1.12	6	0	0	0	0	0	0	0	12782	11810
6/2/2022	0.94	6	0	0	0	0	0	0	0	12782	11810
6/3/2022	1.35	6	0	0	0	0	0	0	0	12782	11810
6/6/2022	1.6	6	0	0	0	0	0	0	0	12782	11810
6/7/2022	1.55	6	0	0	0	0	0	0	0	12782	11810
6/8/2022	1.25	6	0	0	0	0	0	0	0	12782	11810
6/9/2022	1.14	6	0	0	0	0	0	0	0	12782	11810
6/10/2022	0.68	6	0	0	0	0	0	0	0	12782	11810
6/13/2022	0.49	6	0	0	0	0	0	0	0	12782	11810
6/14/2022	0.43	6	0	0	0	0	0	0	0	12782	11810
6/15/2022	0.33	6	0	0	0	0	0	0	0	12782	11810
6/16/2022	0.34	8	0	0	0	0	0	0	0	12782	11810
6/17/2022	0.24	8	0	0	0	0	0	0	0	12782	11810
6/21/2022	0.18	8	0	0	0	0	0	0	0	12782	11810
6/22/2022	0.2	8	0	0	0	0	0	0	0	12782	11810
6/23/2022	0.3	8	0	0	0	0	0	0	0	12782	11810
6/24/2022	0.43	8	0	0	0	0	0	0	0	12782	11810
6/27/2022	0.64	8	0	0	0	0	0	0	0	12782	11810
6/28/2022	0.67	7	0	0	0	0	0	0	0	12782	11810
6/29/2022	0.88	3	-914	-938	6	0	0	-266	-914	11868	10872
6/30/2022	0.73	6	0	0	0	0	0	0	0	11868	10872

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
7/1/2022	1.07	6	0	0	0	0	0	0	0	11868	10872
7/5/2022	1.27	6	0	0	0	0	0	0	0	11868	10872
7/6/2022	1.36	6	0	0	0	0	0	0	0	11868	10872
7/7/2022	1.3	6	0	0	0	0	0	0	0	11868	10872
7/8/2022	1.13	6	0	0	0	0	0	0	0	11868	10872
7/11/2022	1.03	6	0	0	0	0	0	0	0	11868	10872
7/12/2022	1.38	6	0	0	0	0	0	0	0	11868	10872
7/13/2022	1.08	6	0	0	0	0	0	0	0	11868	10872
7/14/2022	1.28	5	809	801	2	809	2	0	0	12677	11673
7/15/2022	1.32	5	-160	-172	3	83	1	-126	-243	12517	11501
7/18/2022	1.26	5	664	656	2	664	2	0	0	13181	12157
7/19/2022	1.58	5	334	322	3	456	1	-108	-122	13515	12479
7/20/2022	1.48	5	177	173	1	177	1	0	0	13692	12652
7/21/2022	1.66	5	-361	-373	3	78	1	-382	-382	13331	12279
7/22/2022	1.5	5	0	0	0	0	0	0	0	13331	12279
7/25/2022	1.38	5	-61	-65	1	0	0	-61	-61	13270	12214
7/26/2022	1.18	5	-35	-47	3	157	1	-160	-192	13235	12167
7/27/2022	1.51	4	223	211	3	541	2	-318	-318	13458	12378
7/28/2022	2.16	4	628	620	2	628	2	0	0	14086	12998
7/29/2022	2.02	4	432	428	1	432	1	0	0	14518	13426
8/1/2022	2.77	4	-325	-345	5	215	2	-301	-535	14193	13081
8/2/2022	1.61	4	-103	-115	3	10	2	-113	-113	14090	12966
8/3/2022	1.35	4	614	610	1	614	1	0	0	14704	13576
8/4/2022	1.61	4	178	174	1	178	1	0	0	14882	13750
8/5/2022	2.27	3	56	44	3	146	2	-90	-90	14938	13794
8/8/2022	2.22	3	552	540	3	606	2	-54	-54	15490	14334
8/9/2022	2.7	2	14	6	2	23	1	-9	-9	15504	14340
8/10/2022	3.02	2	410	398	3	410	3	0	0	15914	14738
8/11/2022	4.05	2	-381	-385	1	0	0	-381	-381	15533	14353
8/12/2022	2.22	2	431	427	1	431	1	0	0	15964	14780
8/15/2022	2.22	2	0	0	0	0	0	0	0	15964	14780
8/16/2022	3.74	1	194	186	2	194	2	0	0	16158	14966
8/17/2022	4.87	1	-121	-129	2	0	0	-87	-121	16037	14837
8/18/2022	3.04	2	0	0	0	0	0	0	0	16037	14837
8/19/2022	2.76	2	84	76	2	199	1	-115	-115	16121	14913
8/22/2022	2.74	2	91	79	3	209	2	-118	-118	16212	14992
8/23/2022	1.97	2	91	87	1	91	1	0	0	16303	15079
8/24/2022	2.09	2	0	0	0	0	0	0	0	16303	15079
8/25/2022	1.53	2	207	203	1	207	1	0	0	16510	15282
8/26/2022	3.76	2	-1109	-1125	4	228	1	-645	-1109	15401	14157
8/29/2022	0.67	2	-532	-544	3	0	0	-204	-532	14869	13613
8/30/2022	0.51	4	-24	-28	1	0	0	-24	-24	14845	13585
8/31/2022	0.42	5	152	140	3	241	2	-89	-89	14997	13725
9/1/2022	0.53	5	76	68	2	161	1	-85	-85	15073	13793

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
9/2/2022	0.58	5	572	560	3	737	2	-165	-165	15645	14353
9/6/2022	0.75	5	-53	-77	6	243	3	-197	-296	15592	14276
9/7/2022	0.72	5	494	490	1	494	1	0	0	16086	14766
9/8/2022	0.91	5	-649	-669	5	35	2	-299	-649	15437	14097
9/9/2022	0.67	5	333	329	1	333	1	0	0	15770	14426
9/12/2022	1.2	4	34	22	3	101	1	-50	-67	15804	14448
9/13/2022	1.66	3	752	740	3	789	2	-37	-37	16556	15188
9/14/2022	2.2	3	62	58	1	62	1	0	0	16618	15246
9/15/2022	2.22	3	128	116	3	196	2	-68	-68	16746	15362
9/16/2022	2.27	3	320	312	2	320	2	0	0	17066	15674
9/19/2022	2.23	3	-92	-100	2	132	1	-224	-224	16974	15574
9/20/2022	1.97	3	-88	-96	2	0	0	-69	-88	16886	15478
9/21/2022	2.11	2	1013	1001	3	1153	2	-140	-140	17899	16479
9/22/2022	2.39	3	-85	-89	1	0	0	-85	-85	17814	16390
9/23/2022	4.35	3	278	270	2	278	2	0	0	18092	16660
9/26/2022	4.28	3	50	46	1	50	1	0	0	18142	16706
9/27/2022	4.64	3	260	240	5	487	3	-131	-131	18402	16946
9/28/2022	3.22	3	447	443	1	447	1	0	0	18849	17389
9/29/2022	3.68	3	402	394	2	402	2	0	0	19251	17783
9/30/2022	4.28	3	506	502	1	506	1	0	0	19757	18285
10/3/2022	4.52	3	451	447	1	451	1	0	0	20208	18732
10/4/2022	6.99	3	0	0	0	0	0	0	0	20208	18732
10/5/2022	8.93	1	0	0	0	0	0	0	0	20208	18732
10/6/2022	7.8	1	0	0	0	0	0	0	0	20208	18732
10/7/2022	5.35	1	0	0	0	0	0	0	0	20208	18732
10/10/2022	5.97	1	0	0	0	0	0	0	0	20208	18732
10/11/2022	4.82	2	635	619	4	635	4	0	0	20843	19351
10/12/2022	7.15	2	0	0	0	0	0	0	0	20843	19351
10/13/2022	4	3	1025	1001	6	1293	4	-163	-196	21868	20352
10/14/2022	3.84	4	-325	-337	3	350	1	-341	-341	21543	20015
10/17/2022	2.3	4	124	112	3	164	2	-40	-40	21667	20127
10/18/2022	2.09	4	86	70	4	444	1	-171	-187	21753	20197
10/19/2022	1.83	4	-136	-148	3	68	2	-204	-204	21617	20049
10/20/2022	1.67	4	102	94	2	262	1	-160	-160	21719	20143
10/21/2022	1.82	4	464	452	3	535	1	-58	-71	22183	20595
10/24/2022	1.71	4	195	187	2	349	1	-154	-154	22378	20782
10/25/2022	1.83	4	63	55	2	207	1	-144	-144	22441	20837
10/26/2022	1.54	4	-47	-55	2	0	0	-35	-47	22394	20782
10/27/2022	1.73	3	-280	-296	4	120	2	-319	-319	22114	20486
10/28/2022	1.11	4	324	312	3	517	1	-167	-193	22438	20798
10/31/2022	1.51	4	-21	-29	2	49	1	-70	-70	22417	20769
11/1/2022	1.42	4	-260	-272	3	180	1	-237	-260	22157	20497
11/2/2022	1.21	4	-191	-207	4	435	2	-358	-358	21966	20290
11/3/2022	1.15	4	364	352	3	364	3	0	0	22330	20642

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
11/4/2022	1.28	4	355	339	4	718	2	-333	-363	22685	20981
11/7/2022	1.21	4	207	203	1	207	1	0	0	22892	21184
11/8/2022	1.23	4	424	416	2	424	2	0	0	23316	21600
11/9/2022	1.41	3	-517	-533	4	0	0	-362	-517	22799	21067
11/10/2022	1.16	4	392	372	5	730	3	-192	-338	23191	21439
11/11/2022	1.42	4	388	384	1	388	1	0	0	23579	21823
11/14/2022	1.48	4	-110	-118	2	0	0	-71	-110	23469	21705
11/15/2022	1.44	4	-140	-160	5	231	4	-371	-371	23329	21545
11/16/2022	1.5	4	0	0	0	0	0	0	0	23329	21545
11/17/2022	1.8	4	110	102	2	176	1	-66	-66	23439	21647
11/18/2022	1.63	4	-97	-105	2	0	0	-66	-97	23342	21542
11/21/2022	1.44	4	107	103	1	107	1	0	0	23449	21645
11/22/2022	1.37	4	395	391	1	395	1	0	0	23844	22036
11/23/2022	1.35	4	0	0	0	0	0	0	0	23844	22036
11/25/2022	2.01	2	0	0	0	0	0	0	0	23844	22036
11/28/2022	1.41	2	0	0	0	0	0	0	0	23844	22036
11/29/2022	1.7	2	28	20	2	28	2	0	0	23872	22056
11/30/2022	4.33	2	478	466	3	629	2	-151	-151	24350	22522
12/1/2022	4.25	2	195	175	5	320	3	-86	-86	24545	22697
12/2/2022	3.97	2	404	396	2	404	2	0	0	24949	23093
12/5/2022	6.82	1	0	0	0	0	0	0	0	24949	23093
12/6/2022	6.43	1	0	0	0	0	0	0	0	24949	23093
12/7/2022	2.85	1	-188	-204	4	46	1	-98	-234	24761	22889
12/8/2022	1.99	4	-44	-52	2	22	1	-66	-66	24717	22837
12/9/2022	1.85	4	0	0	0	0	0	0	0	24717	22837
12/12/2022	1.85	4	0	0	0	0	0	0	0	24717	22837
12/13/2022	1.85	4	408	388	5	660	4	-252	-252	25125	23225
12/14/2022	2.01	4	-171	-183	3	67	1	-140	-238	24954	23042
12/15/2022	1.35	4	-14	-22	2	215	1	-229	-229	24940	23020
12/16/2022	1.15	4	-159	-171	3	79	2	-238	-238	24781	22849
12/19/2022	0.74	4	274	270	1	274	1	0	0	25055	23119
12/20/2022	0.93	4	21	17	1	21	1	0	0	25076	23136
12/21/2022	1.1	3	148	144	1	148	1	0	0	25224	23280
12/22/2022	1.45	2	-377	-389	3	39	1	-295	-416	24847	22891
12/23/2022	1.09	2	261	245	4	360	3	-99	-99	25108	23136
12/27/2022	1.27	3	58	50	2	97	1	-39	-39	25166	23186
12/28/2022	1.03	3	0	0	0	0	0	0	0	25166	23186
12/29/2022	1.21	3	-112	-120	2	135	1	-247	-247	25054	23066
12/30/2022	1.11	3	342	334	2	342	2	0	0	25396	23400
1/3/2023	1.43	3	23	11	3	220	2	-197	-197	25419	23411
1/4/2023	1.34	3	-132	-144	3	32	2	-164	-164	25287	23267
1/5/2023	1.05	3	-506	-522	4	0	0	-204	-506	24781	22745
1/6/2023	0.95	4	460	456	1	460	1	0	0	25241	23201
1/9/2023	1.12	4	-360	-372	3	173	1	-394	-533	24881	22829

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
1/10/2023	0.87	4	-13	-21	2	121	1	-134	-134	24868	22808
1/11/2023	0.83	4	278	274	1	278	1	0	0	25146	23082
1/12/2023	0.99	4	373	357	4	525	3	-152	-152	25519	23439
1/13/2023	1.28	4	173	165	2	284	1	-111	-111	25692	23604
1/17/2023	1.16	4	-124	-128	1	0	0	-124	-124	25568	23476
1/18/2023	1.09	4	-522	-526	1	0	0	-522	-522	25046	22950
1/19/2023	0.88	4	-180	-188	2	0	0	-108	-180	24866	22762
1/20/2023	1.05	4	555	551	1	555	1	0	0	25421	23313
1/23/2023	1.1	4	361	357	1	361	1	0	0	25782	23670
1/24/2023	1.74	4	0	0	0	0	0	0	0	25782	23670
1/25/2023	1.84	4	576	568	2	576	2	0	0	26358	24238
1/26/2023	2.11	4	-83	-103	5	388	2	-165	-471	26275	24135
1/27/2023	1.54	4	0	0	0	0	0	0	0	26275	24135
1/30/2023	1.45	4	-299	-315	4	77	1	-143	-299	25976	23820
1/31/2023	1.17	4	179	175	1	179	1	0	0	26155	23995
2/1/2023	1.38	3	-166	-178	3	235	1	-206	-401	25989	23817
2/2/2023	1.66	3	190	170	5	416	3	-133	-226	26179	23987
2/3/2023	1.89	4	-418	-438	5	372	2	-342	-637	25761	23549
2/6/2023	1.15	4	-242	-254	3	7	1	-190	-249	25519	23295
2/7/2023	0.9	4	1159	1147	3	1265	2	-106	-106	26678	24442
2/8/2023	1.34	4	-472	-480	2	0	0	-437	-472	26206	23962
2/9/2023	0.95	4	-237	-245	2	175	1	-412	-412	25969	23717
2/10/2023	0.9	4	-240	-252	3	0	0	-132	-240	25729	23465
2/13/2023	0.83	4	0	0	0	0	0	0	0	25729	23465
2/14/2023	0.91	4	394	370	6	811	3	-238	-238	26123	23835
2/15/2023	0.99	4	0	0	0	0	0	0	0	26123	23835
2/16/2023	1.05	4	-135	-143	2	0	0	-120	-135	25988	23692
2/17/2023	0.93	4	80	72	2	80	2	0	0	26068	23764
2/21/2023	1.31	4	359	355	1	359	1	0	0	26427	24119
2/22/2023	0.85	4	20	16	1	20	1	0	0	26447	24135
2/23/2023	1.2	4	0	-12	3	52	2	-52	-52	26447	24123
2/24/2023	1.57	4	80	72	2	91	1	-11	-11	26527	24195
2/27/2023	2.3	2	7	-1	2	62	1	-55	-55	26534	24194
2/28/2023	2.2	2	0	0	0	0	0	0	0	26534	24194
3/1/2023	2.62	2	-122	-138	4	53	2	-99	-175	26412	24056
3/2/2023	1.68	2	180	172	2	314	1	-134	-134	26592	24228
3/3/2023	2.41	2	330	326	1	330	1	0	0	26922	24554
3/6/2023	3	2	-137	-141	1	0	0	-137	-137	26785	24413
3/7/2023	2.27	2	46	34	3	124	1	-55	-78	26831	24447
3/8/2023	1.63	3	-49	-53	1	0	0	-49	-49	26782	24394
3/9/2023	1.48	3	1	-3	1	1	1	0	0	26783	24391
3/10/2023	1.53	3	-392	-424	8	185	2	-225	-451	26391	23967
3/13/2023	0.89	4	305	289	4	361	3	-56	-56	26696	24256
3/14/2023	1.13	4	-10	-22	3	141	1	-82	-151	26686	24234

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
3/15/2023	1.11	4	191	183	2	195	1	-4	-4	26877	24417
3/16/2023	1.39	4	519	515	1	519	1	0	0	27396	24932
3/17/2023	1.76	4	129	121	2	129	2	0	0	27525	25053
3/20/2023	1.57	4	278	274	1	278	1	0	0	27803	25327
3/21/2023	2.11	4	169	165	1	169	1	0	0	27972	25492
3/22/2023	2.36	4	-814	-830	4	157	1	-455	-971	27158	24662
3/23/2023	1.21	4	-269	-281	3	167	1	-288	-436	26889	24381
3/24/2023	1.05	4	61	53	2	120	1	-59	-59	26950	24434
3/27/2023	1.33	3	-316	-320	1	0	0	-316	-316	26634	24114
3/28/2023	0.97	3	106	98	2	106	2	0	0	26740	24212
3/29/2023	1.03	3	-46	-54	2	57	1	-103	-103	26694	24158
3/30/2023	0.9	3	45	41	1	45	1	0	0	26739	24199
3/31/2023	0.65	3	0	0	0	0	0	0	0	26739	24199
4/3/2023	0.58	3	-163	-167	1	0	0	-163	-163	26576	24032
4/4/2023	0.4	3	0	0	0	0	0	0	0	26576	24032
4/5/2023	0.32	3	0	0	0	0	0	0	0	26576	24032
4/6/2023	0.46	2	258	250	2	364	1	-106	-106	26834	24282
4/10/2023	0.83	2	428	420	2	428	2	0	0	27262	24702
4/11/2023	2.69	2	0	0	0	0	0	0	0	27262	24702
4/12/2023	2.4	2	-39	-47	2	214	1	-253	-253	27223	24655
4/13/2023	2.01	2	351	347	1	351	1	0	0	27574	25002
4/14/2023	2.6	2	-28	-32	1	0	0	-28	-28	27546	24970
4/17/2023	2.47	2	0	0	0	0	0	0	0	27546	24970
4/18/2023	3.51	1	-99	-107	2	38	1	-137	-137	27447	24863
4/19/2023	2.66	2	135	131	1	135	1	0	0	27582	24994
4/20/2023	2.92	2	0	0	0	0	0	0	0	27582	24994
4/21/2023	2.79	2	-239	-247	2	0	0	-153	-239	27343	24747
4/24/2023	1.77	2	0	0	0	0	0	0	0	27343	24747
4/25/2023	1.12	2	0	0	0	0	0	0	0	27343	24747
4/26/2023	1.12	2	-77	-81	1	0	0	-77	-77	27266	24666
4/27/2023	1.09	3	222	210	3	373	2	-151	-151	27488	24876
4/28/2023	0.86	3	88	84	1	88	1	0	0	27576	24960
5/1/2023	1.05	3	0	0	0	0	0	0	0	27576	24960
5/2/2023	1.05	3	0	0	0	0	0	0	0	27576	24960
5/3/2023	1.28	3	0	0	0	0	0	0	0	27576	24960
5/4/2023	0.99	3	0	0	0	0	0	0	0	27576	24960
5/5/2023	0.99	3	421	417	1	421	1	0	0	27997	25377
5/8/2023	3.87	1	0	0	0	0	0	0	0	27997	25377
5/9/2023	3.87	1	0	0	0	0	0	0	0	27997	25377
5/10/2023	3.87	1	-110	-122	3	126	1	-172	-236	27887	25255
5/11/2023	2.6	2	0	0	0	0	0	0	0	27887	25255
5/12/2023	2.69	2	0	0	0	0	0	0	0	27887	25255
5/15/2023	2.32	2	0	0	0	0	0	0	0	27887	25255
5/16/2023	2.32	2	0	0	0	0	0	0	0	27887	25255

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
5/17/2023	2.32	2	0	0	0	0	0	0	0	27887	25255
5/18/2023	2.32	2	0	0	0	0	0	0	0	27887	25255
5/19/2023	2.32	2	0	0	0	0	0	0	0	27887	25255
5/22/2023	0.53	2	0	0	0	0	0	0	0	27887	25255
5/23/2023	0.53	2	0	0	0	0	0	0	0	27887	25255
5/24/2023	0.53	2	14	10	1	14	1	0	0	27901	25265
5/25/2023	99	0	0	0	0	0	0	0	0	27901	25265
5/26/2023	3.38	2	665	661	1	665	1	0	0	28566	25926
5/30/2023	12.13	2	0	0	0	0	0	0	0	28566	25926
5/31/2023	2.4	2	-20	-24	1	0	0	-20	-20	28546	25902
6/1/2023	2.29	2	218	214	1	218	1	0	0	28764	26116
6/2/2023	2.82	2	136	124	3	332	2	-196	-196	28900	26240
6/5/2023	2.45	2	-41	-45	1	0	0	-41	-41	28859	26195
6/6/2023	2.3	2	-164	-168	1	0	0	-164	-164	28695	26027
6/7/2023	1.84	2	537	529	2	685	1	-148	-148	29232	26556
6/8/2023	2.25	3	283	279	1	283	1	0	0	29515	26835
6/9/2023	2.49	3	-96	-104	2	1	1	-97	-97	29419	26731
6/12/2023	1.57	3	372	368	1	372	1	0	0	29791	27099
6/13/2023	1.95	3	98	86	3	302	2	-204	-204	29889	27185
6/14/2023	2.52	3	115	103	3	193	1	-39	-39	30004	27288
6/15/2023	2.57	3	-8	-12	1	0	0	-8	-8	29996	27276
6/16/2023	2.32	3	0	0	0	0	0	0	0	29996	27276
6/20/2023	2.63	2	47	43	1	47	1	0	0	30043	27319
6/21/2023	3.52	2	0	0	0	0	0	0	0	30043	27319
6/22/2023	3.1	2	198	194	1	198	1	0	0	30241	27513
6/23/2023	2.88	2	194	182	3	225	2	-31	-31	30435	27695
6/26/2023	4.17	2	118	114	1	118	1	0	0	30553	27809
6/27/2023	3.37	2	-554	-562	2	0	0	-490	-554	29999	27247
6/28/2023	1.16	2	-45	-57	3	111	2	-156	-156	29954	27190
6/29/2023	0.93	3	0	0	0	0	0	0	0	29954	27190
6/30/2023	0.94	3	88	76	3	171	2	-83	-83	30042	27266
7/3/2023	1.06	3	0	0	0	0	0	0	0	30042	27266
7/5/2023	1	3	0	0	0	0	0	0	0	30042	27266
7/6/2023	1	3	305	297	2	305	2	0	0	30347	27563
7/7/2023	1.13	3	-123	-127	1	0	0	-123	-123	30224	27436
7/10/2023	0.77	3	153	141	3	234	2	-81	-81	30377	27577
7/11/2023	0.82	3	218	214	1	218	1	0	0	30595	27791
7/12/2023	2.35	2	57	53	1	57	1	0	0	30652	27844
7/13/2023	3.43	2	-310	-318	2	6	1	-316	-316	30342	27526
7/14/2023	1.64	2	0	0	0	0	0	0	0	30342	27526
7/17/2023	1.58	2	221	217	1	221	1	0	0	30563	27743
7/18/2023	2	2	288	284	1	288	1	0	0	30851	28027
7/19/2023	2.56	2	0	0	0	0	0	0	0	30851	28027
7/20/2023	2.56	2	0	0	0	0	0	0	0	30851	28027

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
7/21/2023	1.97	2	-124	-132	2	130	1	-254	-254	30727	27895
7/24/2023	1.77	1	-183	-195	3	45	1	-196	-228	30544	27700
7/25/2023	1.21	2	159	155	1	159	1	0	0	30703	27855
7/26/2023	1.14	2	-422	-438	4	0	0	-199	-422	30281	27417
7/27/2023	0.7	3	-334	-346	3	230	2	-564	-564	29947	27071
7/28/2023	0.73	3	218	206	3	244	2	-26	-26	30165	27277
7/31/2023	0.88	3	0	0	0	0	0	0	0	30165	27277
8/1/2023	0.73	3	0	0	0	0	0	0	0	30165	27277
8/2/2023	0.54	3	-257	-265	2	65	1	-322	-322	29908	27012
8/3/2023	0.48	3	-273	-289	4	83	1	-159	-356	29635	26723
8/4/2023	0.44	4	-641	-653	3	0	0	-323	-641	28994	26070
8/7/2023	0.32	4	127	123	1	127	1	0	0	29121	26193
8/8/2023	0.39	4	340	332	2	340	2	0	0	29461	26525
8/9/2023	0.47	4	0	0	0	0	0	0	0	29461	26525
8/10/2023	0.57	4	739	731	2	739	2	0	0	30200	27256
8/11/2023	1.19	4	-147	-155	2	0	0	-106	-147	30053	27101
8/14/2023	0.92	4	0	0	0	0	0	0	0	30053	27101
8/15/2023	0.92	4	0	0	0	0	0	0	0	30053	27101
8/16/2023	0.92	4	0	0	0	0	0	0	0	30053	27101
8/17/2023	1.13	3	0	0	0	0	0	0	0	30053	27101
8/18/2023	1.53	3	-177	-185	2	41	1	-218	-218	29876	26916
8/21/2023	3.42	3	291	287	1	291	1	0	0	30167	27203
8/22/2023	3.87	3	-310	-314	1	0	0	-310	-310	29857	26889
8/23/2023	1.59	3	409	405	1	409	1	0	0	30266	27294
8/24/2023	2.19	3	645	641	1	645	1	0	0	30911	27935
8/25/2023	2.05	3	181	161	5	438	2	-149	-181	31092	28096
8/28/2023	2.32	2	-61	-65	1	0	0	-61	-61	31031	28031
8/29/2023	2.16	2	0	0	0	0	0	0	0	31031	28031
8/30/2023	2.16	2	-42	-50	2	65	1	-107	-107	30989	27981
8/31/2023	1.98	2	0	0	0	0	0	0	0	30989	27981
9/1/2023	1.98	2	69	65	1	69	1	0	0	31058	28046
9/4/2023	2.61	2	0	0	0	0	0	0	0	31058	28046
9/5/2023	2.21	2	0	0	0	0	0	0	0	31058	28046
9/6/2023	3.83	2	228	224	1	228	1	0	0	31286	28270
9/7/2023	3.4	2	336	328	2	336	2	0	0	31622	28598
9/8/2023	2.67	2	0	0	0	0	0	0	0	31622	28598
9/11/2023	4.15	2	89	85	1	89	1	0	0	31711	28683
9/12/2023	7.36	1	0	0	0	0	0	0	0	31711	28683
9/13/2023	8.97	1	0	0	0	0	0	0	0	31711	28683
9/14/2023	99	0	0	0	0	0	0	0	0	31711	28683
9/15/2023	99	0	0	0	0	0	0	0	0	31711	28683
9/18/2023	99	0	0	0	0	0	0	0	0	31711	28683
9/19/2023	99	0	0	0	0	0	0	0	0	31711	28683

Date	pf	lr	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
9/20/2023	99	0	0	0	0	0	0	0	0	31711	28683
9/21/2023	99	0	0	0	0	0	0	0	0	31711	28683
9/22/2023	5.91	1	0	0	0	0	0	0	0	31711	28683
9/25/2023	6.33	1	0	0	0	0	0	0	0	31711	28683
9/26/2023	6.3	1	0	0	0	0	0	0	0	31711	28683
9/27/2023	5.52	1	0	0	0	0	0	0	0	31711	28683
9/28/2023	2.32	4	-36	-48	3	188	1	-116	-224	31675	28635
9/29/2023	1.61	4	406	398	2	406	2	0	0	32081	29033
10/2/2023	1.57	4	295	283	3	295	3	0	0	32376	29316
10/3/2023	1.96	4	-29	-37	2	141	1	-170	-170	32347	29279
10/4/2023	1.75	4	128	116	3	313	1	-104	-185	32475	29395
10/5/2023	1.48	4	0	0	0	0	0	0	0	32475	29395
10/6/2023	1.79	4	850	842	2	850	2	0	0	33325	30237
10/9/2023	2.63	4	126	118	2	312	1	-186	-186	33451	30355
10/10/2023	2.39	4	0	0	0	0	0	0	0	33451	30355
10/11/2023	2.39	4	7	3	1	7	1	0	0	33458	30358
10/12/2023	3.28	3	-77	-89	3	203	2	-280	-280	33381	30269
10/13/2023	3.08	3	-131	-135	1	0	0	-131	-131	33250	30134
10/16/2023	2.23	3	195	191	1	195	1	0	0	33445	30325
10/17/2023	2.12	3	457	449	2	457	2	0	0	33902	30774
10/18/2023	2.99	2	-480	-496	4	54	1	-212	-480	33422	30278
10/19/2023	1.84	2	-134	-158	6	243	3	-227	-227	33288	30120
10/20/2023	1.54	2	0	0	0	0	0	0	0	33288	30120
10/23/2023	0.98	2	-325	-337	3	27	1	-217	-325	32963	29783
10/24/2023	0.71	2	63	59	1	63	1	0	0	33026	29842
10/25/2023	0.75	2	-383	-391	2	50	1	-433	-433	32643	29451
10/26/2023	0.61	2	421	417	1	421	1	0	0	33064	29868
10/27/2023	0.83	2	-507	-519	3	0	0	-315	-507	32557	29349

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 $b_0+b_1*t+b_2*t^2+b_3*t^3+...b_n*t^n$ 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 are 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 $b_0,b_1,b_2,...,b_n$ 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
$\sum t^2$ 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:

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

Where 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:

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

$$Acceleration(t+1) = d^2P_f/d^2t = 2c_0 + 6d_0*(T+1) + 12e_0*(T+1)^2$$

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 is 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

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

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

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

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 $\mathbf{b_0+b_1*t+b_2*t^2+b_3*t^3+\ldots+b_n*t^n}$ 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 are 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. Once the $\mathbf{b_n}$ coefficients are found using a lookback period of **T** bars to calculate the $\mathbf{b_n}$ 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.

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

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

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	9.3890
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.