Trading QQQ ETF 15min Bars Using the nth Order Fixed Memory Polynomial Velocity Algorithm
Walk Forward in-sample 30 Calendar Days and out-of-sample 7 Calendar days.
1/4/2021 to 4/10/2026 using The Walk Forward Input Explorer
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In previous working papers 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 reason 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 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 15-min bar price data from 1/1/2021 to 4/10/2026.

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 its 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 3^{rd}) 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*** than buy at the market.

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

Intraday Bars Exit Rule:
Close the position at ***1545 EST*** (No trades will be carried out 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 15-minute bar prices of the Invesco QQQ Trust Series ETF traded on the NYSE and known by the symbol QQQ for the 270 weeks/1890 calendar days from January 4, 2021, to April 10, 20264. However, The ***Walk Forward Input Explorer*** will only analyses data from the calendar weeks ending 2/12/2021 to 1/9/2026. The calendar weeks ending 1/16/26 to 4/10/26 will be withheld to see how the filter applied to the 2/12/2021 to 1/9/2026 data did in the next 13 weeks, 3 months of trading of 1/12/26 to 4/10/26. Why did we do this? We wanted to see if the FixmV parameters found in the first section would work on price data it's never seen in the 13 weeks following. In addition, because of the lookback period in TS/MC and the 30 calendar days of the first test period, the week ending 2/05/21 will be the first 30 calendar day test period and the next week ending 2/12/21 will be the first 7 day calendar out-of-sample period.

We will test the FixmVn strategy with the above QQQ ETF 15 min bars on a ***walk forward basis***, where the in-sample (***IS***) will be 30 calendar days, and the out-of-sample (***OOS***) will be the next 7 calendar days following as will be described below.

What Is 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 the 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 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 the 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(standard deviation)*****.**

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 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 1**5 min price bars from 01/04/2021 to 4/10/26 with the following optimization ranges for the FixmVn strategy inputs. This will create **270, 30 day in-sample periods each followed by a 1 week 7 calendar day out-of-sample period** (See Figure 1 for the in-sample/out-of-sample periods).

The optimization ranges are:

1. **pw=degree from 1 to 3**
2. **N from 4 to 60 in steps of 4.**
3. **vup from 0.5 to 3.5 steps of 0.50**
4. **vdn from 0.5 to 3.5 in steps of 0.50**
5. **open from 9:45 to 10:00 in steps of 15 min**
6. **close trade at 1545**

7. **Mult = 7.63, iNorm=1 (See Appendix 3, the Normalization Multiplier)**

The above pw, n, vup, vdn, open will produce 4410 different input combinations or cases of the strategy input parameters for each of the 270 in-sample/out-of-sample files for the 5+ years 15 min bar QQQ data.

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 for 30 calendar days, and the out-of-sample section is the next trading week. 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 week. If the strategy inputs do not satisfy the in-sample metric filter, ***we do not trade next week***.

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 in-sample 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 strategy 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≤50 to 70 step 10.** We will also look at the strategy inputs with no metric-filter. With 4410 different strategy input combinations times 60 pf,lr,r2,none combinations will give us 264600 **strategy input|metric-filter** combinations. Each one of these 264600-strategy **input|metric-filter** combinations will be applied to each in-sample section and their out-of-sample performance will be tabulated for 257 PWFO files for 01/04/21-01/9/26. The 13 weekly PWFO files between 01/9/26-4/10/26 were not included because they will be used to see how the strategy input/filter does on non-tested prices.

Below is a snippet of the output from a run of all 264599 combinations sorted by **tONP(the out-of-sample 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 FixmVn that was run on 100 shares of QQQ ETF 15-minute bars 257 weeks from 01/04/2021 to 1/9/2026. The in-sample (IS) period is 30 calendar trading days, and the out-of-sample (OOS) period is 1 calendar week trading days. This strategy was traded between 9:45am to 1545pm Exchange Time (EST). The next section on each input line is how the ***Filter*** did on the next 13 weeks from 1/9/2026 to 4/10/2026. This section of data was not involved in the Walk Forward Input Explorer filter selection from 1/4/2021 to 1/9/2026.

From this run, we chose the filter on row 6 of the Figure below. That is,

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Row 6, 1|4|1.5|3|945|1545|7.63|pf<2|r2<70. This is constructed as follows.
For the strategy inputs **1|4|1.5|3|945|1545|** only those in-sample sections that have a **pf≤2 and r2≤70** is used to trade in the following out-of-sample next trading week section. If the in-sample pf>2 or r2>70, then the next trading week out-of-sample section ***is not*** traded. We chose this row because it had the highest **t** and lowest **BE**,

	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	QQQ15mFixnV30x7b	s02/12/21	e01/09/26	#257	AnyTnp	#13					ISnt2			a(5.2)	s32.5						c=$4				
2	pw|N|vup|vdn|xopn|xt|mult|<PF<LR<R2	toGP	tONP	aoGP	aoTr	ao#T	#	%P	oW|oL	%Wtr	std	skew	kur	t	LLtr	LLp	eqDD	wpr	lpr	V20	KTau	eqR2	Blw	BE	tkr|blbe
3	1|4|1.5|3|945|1545|7.63|pf<5|r2<70	31877	29677	179	58	3.1	178	66	1.01	59	660	0.446	8.66	3.62	-2911	-2238	-4507	13	5	116	91	94	27	82	1383
4	1|4|1.5|3|945|1545|7.63|r2<70	31877	29677	179	58	3.1	178	66	1.01	59	660	0.446	8.66	3.62	-2911	-2238	-4507	13	5	116	91	94	27	82	1383
5	1|4|1.5|3|945|1545|7.63|pf<4|r2<70	31451	29275	179	57.8	3.1	176	66	1.01	59	663	0.445	8.58	3.57	-2911	-2238	-4507	13	5	116	90	93	28	85	1265
6	1|4|1.5|3|945|1545|7.63|pf<2|r2<70	30751	28827	204	63.9	3.2	151	66	1.04	59	651	0.931	9.01	3.84	-2911	-2238	-3636	10	4	188	87	91	28	73	1491
7	1|4|1.5|3|945|1545|7.63|pf<3|r2<70	30473	28345	179	57.3	3.1	170	66	1.02	58	672	0.44	8.42	3.48	-2911	-2238	-4507	11	5	116	90	92	28	89	1149
8	1|4|1.5|3|945|1545|7.63|pf<2|	30362	28318	190	59.4	3.2	160	66	1.02	59	653	0.816	8.79	3.68	-2911	-2238	-3636	10	3	203	80	86	39	80	822
9	1|4|1.5|3|945|1545|7.63|lr<5r2<70	30065	27957	176	57	3.1	171	65	1.02	58	669	0.461	8.56	3.44	-2911	-2238	-4694	13	7	110	91	93	27	91	1180
10	1|4|1.5|3|945|1545|7.63|pf<5|lr<5r2<70	30065	27957	176	57	3.1	171	65	1.02	58	669	0.461	8.56	3.44	-2911	-2238	-4694	13	7	110	91	93	27	91	1180
11	1|4|1.5|3|945|1545|7.63|pf<4|lr<5r2<70	29639	27555	175	56.9	3.1	169	65	1.02	58	672	0.461	8.47	3.39	-2911	-2238	-4694	13	7	110	90	93	28	94	1077
12	1|4|1.5|3|945|1545|7.63|pf<2|lr<5r2<70	28939	27107	201	63.2	3.2	144	65	1.05	59	661	0.948	8.9	3.65	-2911	-2238	-3636	10	6	183	87	91	28	81	1267
13	1|4|1.5|3|945|1545|7.63|pf<3|lr<5r2<70	28661	26625	176	56.3	3.1	163	65	1.02	58	682	0.456	8.31	3.29	-2911	-2238	-4694	11	7	110	89	92	28	100	972
14	1|4|1.5|3|945|1545|7.63|pf<2|lr<5	28550	26598	187	58.5	3.2	153	65	1.03	58	662	0.833	8.68	3.49	-2911	-2238	-3636	10	4	197	80	86	39	89	695
15	1|4|1.5|3|945|1545|7.63|pf<2|r2<60	26885	25049	187	58.6	3.2	144	64	1.03	58	657	0.993	9.16	3.41	-2911	-2238	-3636	10	4	178	86	89	30	93	939
16	3|4|2|3|945|1545|7.63|pf<4|r2<70	36150	24930	173	12.9	13.4	209	60	1.23	49	866	0.631	7.68	2.89	-1255	-1976	-7222	5	5	293	88	95	28	129	671
17	3|4|2|3|945|1545|7.63|pf<3|r2<70	36150	24930	173	12.9	13.4	209	60	1.23	49	866	0.631	7.68	2.89	-1255	-1976	-7222	5	5	293	88	95	28	129	671
18	3|4|2|3|945|1545|7.63|r2<70	36150	24930	173	12.9	13.4	209	60	1.23	49	866	0.631	7.68	2.89	-1255	-1976	-7222	5	5	293	88	95	28	129	671
19	3|4|2|3|945|1545|7.63|pf<5|r2<70	36150	24930	173	12.9	13.4	209	60	1.23	49	866	0.631	7.68	2.89	-1255	-1976	-7222	5	5	293	88	95	28	129	671
20	2|32|0.5|2.5|945|1545|7.63|pf<2|	27159	24227	134	37.1	3.6	203	59	0.95	58	595	0.314	4.4	3.2	-1970	-1451	-2765	8	5	142	93	97	17	105	1627

1	QQQ15mFixnV30x7b	s01/16/26	e04/10/26	#13			f264599	
2	pw|N|vup|vdn|xopn|xt|mult|<PF<LR<R2	toGPx	toNPx	aoTRx	aoNTx	#x	tOnpNet	Prob
3	1|4|1.5|3|945|1545|7.63|pf<5|r2<70	873	589	12	5.5	13	30266	6.21E-08
4	1|4|1.5|3|945|1545|7.63|r2<70	873	589	12	5.5	13	30266	6.21E-08
5	1|4|1.5|3|945|1545|7.63|pf<4|r2<70	873	589	12	5.5	13	29864	6.63E-08
6	1|4|1.5|3|945|1545|7.63|pf<2|r2<70	1771	1499	26	5.7	12	30326	8.16E-10
7	1|4|1.5|3|945|1545|7.63|pf<3|r2<70	873	589	12	5.5	13	28934	6.20E-08
8	1|4|1.5|3|945|1545|7.63|pf<2|	1771	1499	26	5.7	12	29817	1.06E-08
9	1|4|1.5|3|945|1545|7.63|lr<5r2<70	873	589	12	5.5	13	28546	1.07E-07
10	1|4|1.5|3|945|1545|7.63|pf<5|lr<5r2<70	873	589	12	5.5	13	28546	1.07E-07
11	1|4|1.5|3|945|1545|7.63|pf<4|lr<5r2<70	873	589	12	5.5	13	28144	1.15E-07
12	1|4|1.5|3|945|1545|7.63|pf<2|lr<5r2<70	1771	1499	26	5.7	12	28606	1.35E-09
13	1|4|1.5|3|945|1545|7.63|pf<3|lr<5r2<70	873	589	12	5.5	13	27214	1.09E-07
14	1|4|1.5|3|945|1545|7.63|pf<2|lr<5	1771	1499	26	5.7	12	28097	1.84E-08
15	1|4|1.5|3|945|1545|7.63|pf<2|r2<60	1771	1499	26	5.7	12	26548	1.80E-08
16	3|4|2|3|945|1545|7.63|pf<4|r2<70	(2621)	(3941)	(8)	25.4	13	20989	6.46E-05
17	3|4|2|3|945|1545|7.63|pf<3|r2<70	(2621)	(3941)	(8)	25.4	13	20989	6.46E-05
18	3|4|2|3|945|1545|7.63|r2<70	(2621)	(3941)	(8)	25.4	13	20989	6.46E-05
19	3|4|2|3|945|1545|7.63|pf<5|r2<70	(2621)	(3941)	(8)	25.4	13	20989	6.46E-05
20	2|32|0.5|2.5|945|1545|7.63|pf<2|	(6244)	(6464)	(114)	4.6	12	17763	6.41E-05

This is the 2nd section from 1/16/2026 to 4/10/2026 which was not included in the Walk Forward Input Explorer(WFINP) run. This is how the filter found by the WFINP on the 1/4/2021-01/9/26 data performed on the next 13-calendar week trading days. Also notice that pw's of 2 and 3 produced negative results in the next 13 weeks

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 257 out-of-sample files of **($5.2)** with a bootstrap standard deviation of **$32.5**. (Side Note. The average is the average per out-of-sample period. So, the average for the random selection would be the random toNP/257 and the average for the filter would be the filter toNP/# of OOS periods traded or 28827/151=190.9). The probability of obtaining our filters average daily net profit **of 190.9** is **$8.16x10^{-10}$** which is **6.03** standard deviations from the bootstrap average. For our filter, in row 6 above, the expected number of cases that we could obtain by pure chance that would match or exceed **$190.9** is $[1-(1-\mathbf{8.16x10^{-10}})^{264599}\mathbf{]} \sim$ **$264599*8.16^{-10}$** = **0.000216** where **264599** is the total number of different strategy inputs and 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 270 calendar weeks from 2/12/21 to 4/10/26. Separated by a red line from the data from 13 trading weeks from 1/16/26 to 4/10/26 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 weekly 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 3/18/2026-4/10/2026.

Table 1 below presents a table of the 270 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 13 trading weeks from 1/16/26 to 4/10/26 that were not included in the WFINP filter that was run from 1/4/21 – 1/9/26.

Discussion of Strategy Performance

In Figure 3, Row 6 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 weeks the OSNP equity curve failed to make a new high. **Blw** is **28** weeks for this filter. This means that 28 trading weeks were 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=59%**. **%P** is the % winning oos weeks, **%P=66%**. The average oos winning trade to the average oos losing trade ratio(**oW|oL**) was **1.04**. **wpr=10** is the maximum number of consecutive winning oos weeks in a row and **lpr=4** is the maximum number of consecutive losing oos weeks in a row. The Largest losing trade in the 1/4/21-1/9/26 period was ($2911) and the largest losing week was ($3636). The average net week was $190.9 @ 3.2 average trades on weeks that it traded for the 1/4/26-1/9/26 period.

In Figure 1, which presents a graph of the equity curve using the filter on the 270 trading days of out-of-sample data, notice how the equity curve follows the 2nd order polynomial trend line with an R^2 of 0.909. The R^2 only dropped to 0.899 for the net equity curve.

Using this filter, the strategy was able to generate $28827 net equity after commissions of $0 (many brokers today, don't charge commissions) and roundtrip slippage of $4 trading 100 QQQ ETF shares for 257 weeks. The filter generated an extra $1499 net equity for the weeks between 1/16/26 to 4/10/26, the data that was not included in the WFINP filter run for a total of $30236 net equity. This period from 12/21 to 12/23 was a volatile down then after anup 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 no trades/week to a high of 14 trades/week with an average of 3.2 trades/week on the weeks it traded. For the no trade weeks, the strategy **input|filte**r in the in-sample section didn't satisfy the metric filter or vup/vdn levels the next week so no trades were made the next trading week. The **input|filter** traded 151 weeks out of the 257 weeks or 58% of the time. For the 1/16/26-4/10/26 period the **input|filter** traded 12 weeks out of 13 or 92% 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 week on the in-sample section on QQQ 15min Bar Prices 01/12/2021 to 1/9/2026 Not Included in WFINP run 1/9/26-4/10/26

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.

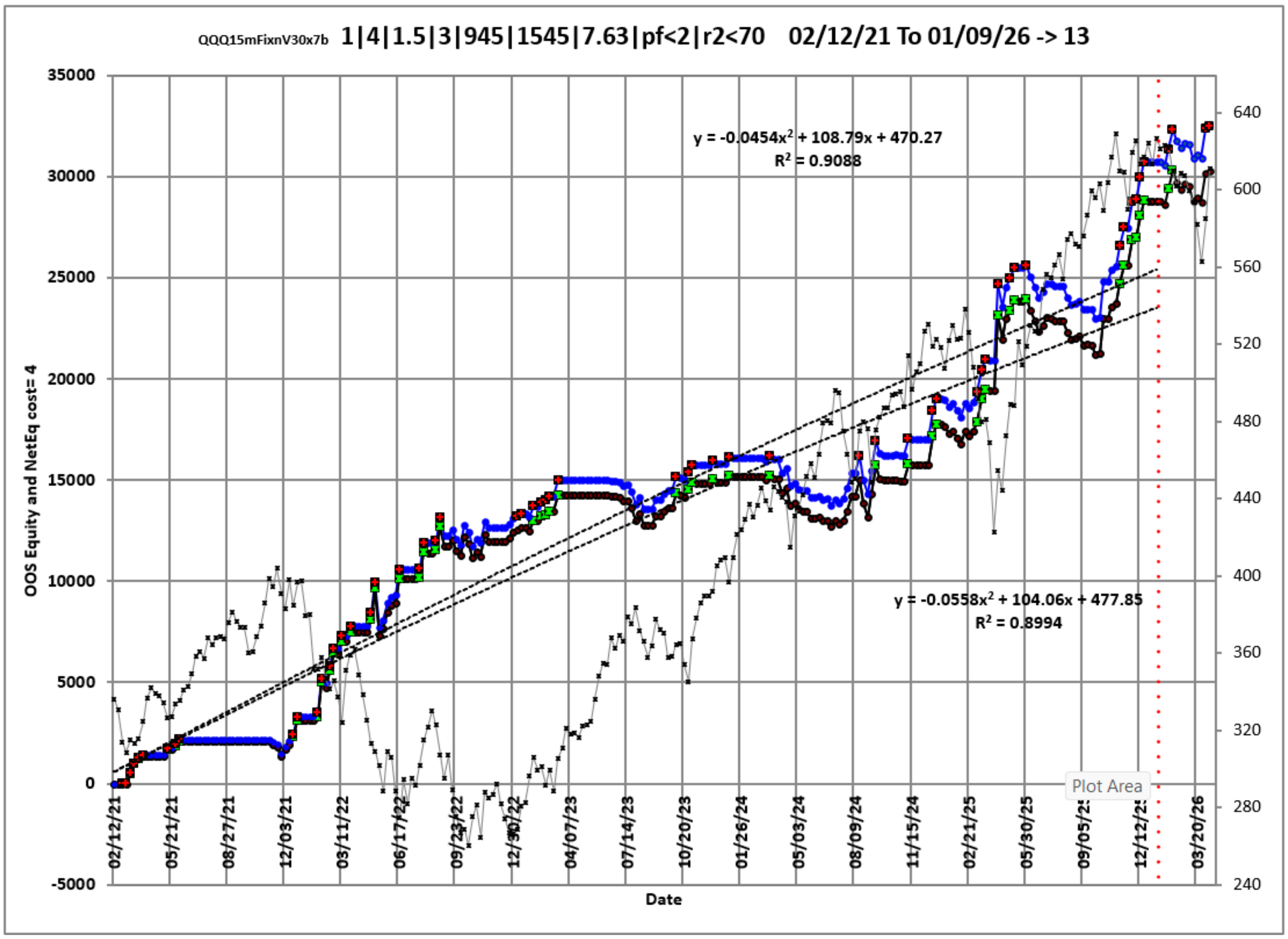

Figure 2 Walk Forward Out-Of-Sample Performance Summary for nth Order Fixed Memory Polynomial Velocity Strategy QQQ 5-minute bar chart from 3/18/26 to 4/10/26

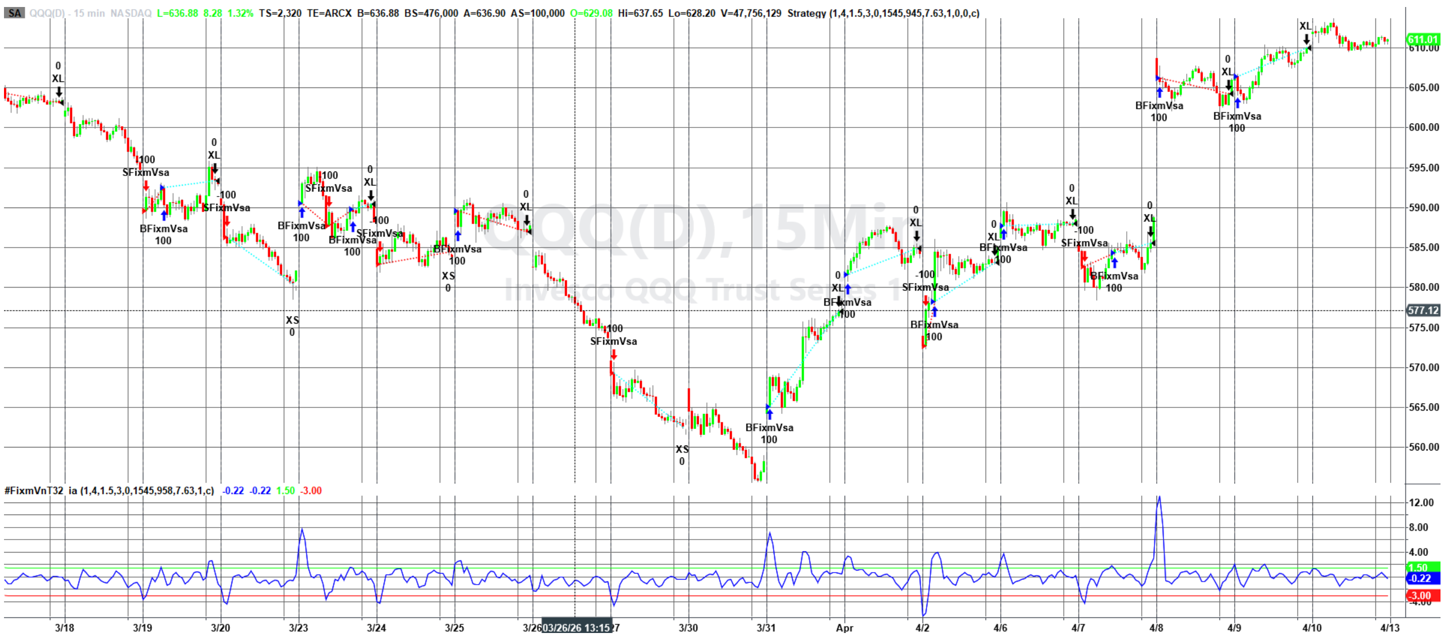

Figure 3 Partial output of the Walk Forward Strategy Inputs with Metric Filters (WFINP) QQQ ETF 15 min bars Using the FixmVn Strategy

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></tr>
<tr><td>1</td><td>QQQ15mFixnV30x7b</td><td>s02/12/21</td><td>e01/09/26</td><td>#257</td><td>AnyTnp</td><td>#13</td><td></td><td></td><td></td><td></td><td>ISnt2</td><td></td><td></td><td>a(5.2)</td><td>s32.5</td><td></td><td></td><td></td><td></td><td></td><td>c=$4</td><td></td><td></td><td></td><td></td></tr>
<tr><td>2</td><td>pw|N|vup|vdn|xopn|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>%P</td><td>oW|oL</td><td>%Wtr</td><td>std</td><td>skew</td><td>kur</td><td>t</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|blbe</td></tr>
<tr><td>3</td><td>1|4|1.5|3|945|1545|7.63|pf<5|r2<70</td><td>31877</td><td>29677</td><td>179</td><td>58</td><td>3.1</td><td>178</td><td>66</td><td>1.01</td><td>59</td><td>660</td><td>0.446</td><td>8.66</td><td>3.62</td><td>-2911</td><td>-2238</td><td>-4507</td><td>13</td><td>5</td><td>116</td><td>91</td><td>94</td><td>27</td><td>82</td><td>1383</td></tr>
<tr><td>4</td><td>1|4|1.5|3|945|1545|7.63|r2<70</td><td>31877</td><td>29677</td><td>179</td><td>58</td><td>3.1</td><td>178</td><td>66</td><td>1.01</td><td>59</td><td>660</td><td>0.446</td><td>8.66</td><td>3.62</td><td>-2911</td><td>-2238</td><td>-4507</td><td>13</td><td>5</td><td>116</td><td>91</td><td>94</td><td>27</td><td>82</td><td>1383</td></tr>
<tr><td>5</td><td>1|4|1.5|3|945|1545|7.63|pf<4|r2<70</td><td>31451</td><td>29275</td><td>179</td><td>57.8</td><td>3.1</td><td>176</td><td>66</td><td>1.01</td><td>59</td><td>663</td><td>0.445</td><td>8.58</td><td>3.57</td><td>-2911</td><td>-2238</td><td>-4507</td><td>13</td><td>5</td><td>116</td><td>90</td><td>93</td><td>28</td><td>85</td><td>1265</td></tr>
<tr><td>6</td><td>1|4|1.5|3|945|1545|7.63|pf<2|r2<70</td><td>30751</td><td>28827</td><td>204</td><td>63.9</td><td>3.2</td><td>151</td><td>66</td><td>1.04</td><td>59</td><td>651</td><td>0.931</td><td>9.01</td><td>3.84</td><td>-2911</td><td>-2238</td><td>-3636</td><td>10</td><td>4</td><td>188</td><td>87</td><td>91</td><td>28</td><td>73</td><td>1491</td></tr>
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<tr><td>10</td><td>1|4|1.5|3|945|1545|7.63|pf<5|lr<5r2<70</td><td>30065</td><td>27957</td><td>176</td><td>57</td><td>3.1</td><td>171</td><td>65</td><td>1.02</td><td>58</td><td>669</td><td>0.461</td><td>8.56</td><td>3.44</td><td>-2911</td><td>-2238</td><td>-4694</td><td>13</td><td>7</td><td>110</td><td>91</td><td>93</td><td>27</td><td>91</td><td>1180</td></tr>
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<tr><td>19</td><td>3|4|2|3|945|1545|7.63|pf<5|r2<70</td><td>36150</td><td>24930</td><td>173</td><td>12.9</td><td>13.4</td><td>209</td><td>60</td><td>1.23</td><td>49</td><td>866</td><td>0.631</td><td>7.68</td><td>2.89</td><td>-1255</td><td>-1976</td><td>-7222</td><td>5</td><td>5</td><td>293</td><td>88</td><td>95</td><td>28</td><td>129</td><td>671</td></tr>
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<tr><td>2</td><td>pw|N|vup|vdn|xopn|xt|mult|<PF<LR<R2</td><td>toGPx</td><td>toNPx</td><td>aoTRx</td><td>aoNTx</td><td>#x</td><td>tOnpNet</td><td>Prob</td></tr>
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<tr><td>17</td><td>3|4|2|3|945|1545|7.63|pf<3|r2<70</td><td>(2621)</td><td>(3941)</td><td>(8)</td><td>25.4</td><td>13</td><td>20989</td><td>6.46E-05</td></tr>
<tr><td>18</td><td>3|4|2|3|945|1545|7.63|r2<70</td><td>(2621)</td><td>(3941)</td><td>(8)</td><td>25.4</td><td>13</td><td>20989</td><td>6.46E-05</td></tr>
<tr><td>19</td><td>3|4|2|3|945|1545|7.63|pf<5|r2<70</td><td>(2621)</td><td>(3941)</td><td>(8)</td><td>25.4</td><td>13</td><td>20989</td><td>6.46E-05</td></tr>
<tr><td>20</td><td>2|32|0.5|2.5|945|1545|7.63|pf<2|</td><td>(6244)</td><td>(6464)</td><td>(114)</td><td>4.6</td><td>12</td><td>17763</td><td>6.41E-05</td></tr>
</table>

The WFINP AVE File Output Cols are defined as follows.

Row 1 QQQ15Fixm30x7b are the PWFO output files abbreviation, First OOS Day End Date (2/12/21), Last OOS Day End Date (1/9/26), **Number of weeks** (#257) 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 6: **1|4|1.5|3|945|1545|7.63|pf<2|r2<70 :** The inputs **1|4|1.5|3|945|1545|7.63** for all in-sample files that have **pf<2 and r2≤70**.
Col B: ***toGP*** Total out-of-sample(oos) gross profit for these 257 oos periods (for this run periods = weeks).
Col C: ***toNP*** Total out-of-sample(oos) Net profit (toGP-(# of Trade days)*cost) for the 257 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 statistics 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.
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|blbe*** =100*t*Ktau*eqR2/(Blw*BE). This is a 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 weekly results from 1/16/26-4/10/26 that were not included in the filter scan from 1/4/21 to 1/9/26.

Col AB: ***toGPx*** Total gross profit for the 13 excluded periods (for this run periods = weeks).
Col AC: ***toNPx*** Total Net profit for the 13 excluded periods.
Col AD: ***aoTrx*** Average profit per trade for the 13 excluded periods
Col AE: ***aoNTx*** Average number of trades per week for the 13 excluded periods
Col AF: ***#x*** the number of the 13 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 excluded periods

Table 1 Walk Forward Out-Of-Sample Performance Summary for the QQQ 15-min FixmVn Strategy

QQQ-15 min bars 02/12/2021 - 4/10/2026.

Filter: **1|4|1.5|3|945|1545|7.63|pf<2|r2<70;** The inputs **1|4|1.5|3|945|1545|7.63** for all in-sample files that have **pf≤2 and r2≤70**.
are used to trade in the following out-of-sample sections.

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

Date	In-samp pf	In-samp r2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
2/12/2021	0.51	0.86	0	0	0	0	0	0	0	0	0
2/19/2021	0.34	-86	0	0	0	0	0	0	0	0	0
2/26/2021	0.18	-80	12	0	3	498	2	(486)	(486)	12	0
3/5/2021	0.68	-16	6	(10)	4	1140	2	(568)	(1134)	18	-10
3/12/2021	1.01	0	489	477	3	825	2	(336)	(336)	507	467
3/19/2021	1.26	26	499	487	3	568	2	(69)	(69)	1006	954
3/26/2021	1.5	52	236	228	2	236	2	0	0	1242	1182
4/2/2021	1.83	63	169	161	2	169	2	0	0	1411	1343
4/9/2021	2.64	87	0	0	0	0	0	0	0	1411	1343
4/16/2021	23.72	94	0	0	0	0	0	0	0	1411	1343
4/23/2021	99	98	0	0	0	0	0	0	0	1411	1343
4/30/2021	99	96	0	0	0	0	0	0	0	1411	1343
5/7/2021	99	91	0	0	0	0	0	0	0	1411	1343
5/14/2021	1.51	1	342	330	3	342	3	0	0	1753	1673
5/21/2021	2.08	1	0	0	0	0	0	0	0	1753	1673
5/28/2021	1.41	16	195	191	1	195	1	0	0	1948	1864
6/4/2021	1.75	36	221	217	1	221	1	0	0	2169	2081
6/11/2021	4.06	80	0	0	0	0	0	0	0	2169	2081
6/18/2021	3.71	83	0	0	0	0	0	0	0	2169	2081
6/25/2021	61	80	0	0	0	0	0	0	0	2169	2081
7/2/2021	3.1	-49	0	0	0	0	0	0	0	2169	2081
7/9/2021	6.88	51	0	0	0	0	0	0	0	2169	2081
7/16/2021	4.01	62	0	0	0	0	0	0	0	2169	2081
7/23/2021	4.48	100	0	0	0	0	0	0	0	2169	2081
7/30/2021	4.48	100	0	0	0	0	0	0	0	2169	2081
8/6/2021	3.13	-100	0	0	0	0	0	0	0	2169	2081
8/13/2021	1.11	100	0	0	0	0	0	0	0	2169	2081
8/20/2021	1.11	100	0	0	0	0	0	0	0	2169	2081
8/27/2021	3.09	97	0	0	0	0	0	0	0	2169	2081
9/3/2021	99	92	0	0	0	0	0	0	0	2169	2081
9/10/2021	99	97	0	0	0	0	0	0	0	2169	2081
9/17/2021	99	97	0	0	0	0	0	0	0	2169	2081
9/24/2021	99	97	0	0	0	0	0	0	0	2169	2081
10/1/2021	30.78	74	0	0	0	0	0	0	0	2169	2081
10/8/2021	2.59	27	0	0	0	0	0	0	0	2169	2081
10/15/2021	3.9	79	0	0	0	0	0	0	0	2169	2081
10/22/2021	4.36	84	0	0	0	0	0	0	0	2169	2081

Date	In-samp pf	In-samp r2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
10/29/2021	3.71	88	0	0	0	0	0	0	0	2169	2081
11/5/2021	6.25	76	0	0	0	0	0	0	0	2169	2081
11/12/2021	0.96	2	(127)	(135)	2	30	1	(157)	(157)	2042	1946
11/19/2021	0.87	-74	(107)	(111)	1	0	0	(107)	(107)	1935	1835
11/26/2021	0.28	-75	(492)	(500)	2	29	1	(521)	(521)	1443	1335
12/3/2021	0.2	-88	359	339	5	1007	3	(626)	(648)	1802	1674
12/10/2021	0.75	-52	273	269	1	273	1	0	0	2075	1943
12/17/2021	0.93	-6	357	345	3	555	2	(198)	(198)	2432	2288
12/24/2021	1.26	42	855	839	4	855	4	0	0	3287	3127
12/31/2021	3.18	83	0	0	0	0	0	0	0	3287	3127
1/7/2022	13.01	96	0	0	0	0	0	0	0	3287	3127
1/14/2022	4.18	89	0	0	0	0	0	0	0	3287	3127
1/21/2022	3.66	92	0	0	0	0	0	0	0	3287	3127
1/28/2022	0.72	-4	195	163	8	2007	4	(721)	(1769)	3482	3290
2/4/2022	0.77	-37	1716	1696	5	1716	5	0	0	5198	4986
2/11/2022	1.15	-9	(215)	(227)	3	492	2	(707)	(707)	4983	4759
2/18/2022	0.98	3	811	799	3	811	3	0	0	5794	5558
2/25/2022	1.19	51	893	877	4	1689	2	(497)	(796)	6687	6435
3/4/2022	2.34	77	0	0	0	0	0	0	0	6687	6435
3/11/2022	1.81	51	605	585	5	770	3	(144)	(165)	7292	7020
3/18/2022	1.45	75	0	0	0	0	0	0	0	7292	7020
3/25/2022	1.73	63	467	455	3	624	2	(157)	(157)	7759	7475
4/1/2022	2.04	66	0	0	0	0	0	0	0	7759	7475
4/8/2022	2.64	69	0	0	0	0	0	0	0	7759	7475
4/15/2022	1.9	82	0	0	0	0	0	0	0	7759	7475
4/22/2022	2.64	79	0	0	0	0	0	0	0	7759	7475
4/29/2022	1	8	680	652	7	2199	4	(595)	(1519)	8439	8127
5/6/2022	1.01	-39	1527	1503	6	2183	3	(402)	(483)	9966	9630
5/13/2022	1.35	11	(2238)	(2278)	10	1065	2	(663)	(3303)	7728	7352
5/20/2022	0.83	1	325	313	3	964	2	(639)	(639)	8053	7665
5/27/2022	0.86	0	854	838	4	1102	3	(248)	(248)	8907	8503
6/3/2022	1.4	-16	327	311	4	816	2	(447)	(489)	9234	8814
6/10/2022	0.95	-26	119	107	3	458	2	(339)	(339)	9353	8921
6/17/2022	1.21	70	1232	1216	4	1235	3	(3)	(3)	10585	10137
6/24/2022	2.1	87	0	0	0	0	0	0	0	10585	10137
7/1/2022	3.25	86	0	0	0	0	0	0	0	10585	10137
7/8/2022	3.53	78	0	0	0	0	0	0	0	10585	10137
7/15/2022	4.67	55	0	0	0	0	0	0	0	10585	10137
7/22/2022	1.69	13	49	37	3	646	2	(597)	(597)	10634	10174
7/29/2022	1.46	3	1270	1258	3	1270	3	0	0	11904	11432
8/5/2022	2.33	48	0	0	0	0	0	0	0	11904	11432
8/12/2022	2.05	67	0	0	0	0	0	0	0	11904	11432
8/19/2022	1.44	57	94	90	1	94	1	0	0	11998	11522
8/26/2022	1.68	-5	1164	1152	3	1164	3	0	0	13162	12674
9/2/2022	2	15	(913)	(921)	2	0	0	(637)	(913)	12249	11753
9/9/2022	0.9	41	27	15	3	404	1	(221)	(377)	12276	11768
9/16/2022	1.16	6	260	244	4	764	1	(311)	(500)	12536	12012
9/23/2022	1.35	3	(456)	(472)	4	230	1	(542)	(542)	12080	11540
9/30/2022	0.88	-15	(260)	(276)	4	601	2	(524)	(861)	11820	11264
10/7/2022	0.65	-26	976	964	3	976	3	0	0	12796	12228
10/14/2022	1.31	-4	(349)	(365)	4	704	1	(667)	(1053)	12447	11863
10/21/2022	0.86	5	(693)	(713)	5	491	2	(418)	(1184)	11754	11150
10/28/2022	0.86	0	350	330	5	831	3	(248)	(481)	12104	11480
11/4/2022	1.16	-17	(204)	(220)	4	370	2	(542)	(542)	11900	11260
11/11/2022	0.87	-34	1047	1035	3	1047	3	0	0	12947	12295
11/18/2022	1.18	6	(300)	(308)	2	0	0	(207)	(300)	12647	11987
11/25/2022	1.49	54	0	0	0	0	0	0	0	12647	11987
12/2/2022	2.04	66	0	0	0	0	0	0	0	12647	11987
12/9/2022	2.96	79	0	0	0	0	0	0	0	12647	11987
12/16/2022	2.84	38	0	0	0	0	0	0	0	12647	11987
12/23/2022	0.99	-17	202	190	3	285	1	(49)	(49)	12849	12177
12/30/2022	1.26	-35	257	253	1	257	1	0	0	13106	12430

Date	In-samp pf	In-samp r2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
1/6/2023	0.83	-3	134	126	2	605	1	(471)	(471)	13240	12556
1/13/2023	1.18	22	97	85	3	331	2	(234)	(234)	13337	12641
1/20/2023	2.3	65	0	0	0	0	0	0	0	13337	12641
1/27/2023	2	44	(154)	(166)	3	405	2	(559)	(559)	13183	12475
2/3/2023	1.26	20	543	535	2	543	2	0	0	13726	13010
2/10/2023	2.38	34	0	0	0	0	0	0	0	13726	13010
2/17/2023	0.65	-35	197	189	2	197	2	0	0	13923	13199
2/24/2023	0.69	-54	105	97	2	105	2	0	0	14028	13296
3/3/2023	0.83	-56	167	159	2	282	1	(115)	(115)	14195	13455
3/10/2023	0.62	-32	0	0	0	0	0	0	0	14195	13455
3/17/2023	0.79	67	810	798	3	838	2	(28)	(28)	15005	14253
3/24/2023	8.57	83	0	0	0	0	0	0	0	15005	14253
3/31/2023	4	88	0	0	0	0	0	0	0	15005	14253
4/7/2023	6.07	79	0	0	0	0	0	0	0	15005	14253
4/14/2023	4.96	69	0	0	0	0	0	0	0	15005	14253
4/21/2023	5.68	55	0	0	0	0	0	0	0	15005	14253
4/28/2023	2.39	85	0	0	0	0	0	0	0	15005	14253
5/5/2023	4.62	77	0	0	0	0	0	0	0	15005	14253
5/12/2023	6.36	78	0	0	0	0	0	0	0	15005	14253
5/19/2023	7.05	87	0	0	0	0	0	0	0	15005	14253
5/26/2023	5.16	92	0	0	0	0	0	0	0	15005	14253
6/2/2023	99	92	0	0	0	0	0	0	0	15005	14253
6/9/2023	3.77	61	0	0	0	0	0	0	0	15005	14253
6/16/2023	1.68	-3	(35)	(39)	1	0	0	(35)	(35)	14970	14214
6/23/2023	1.57	-13	0	0	0	0	0	0	0	14970	14214
6/30/2023	1.57	-13	(48)	(56)	2	134	1	(182)	(182)	14922	14158
7/7/2023	0.31	-66	(174)	(178)	1	0	0	(174)	(174)	14748	13980
7/14/2023	0.25	-62	29	17	3	399	2	(370)	(370)	14777	13997
7/21/2023	0.73	6	(333)	(337)	1	0	0	(333)	(333)	14444	13660
7/28/2023	0.5	-11	(617)	(629)	3	237	2	(854)	(854)	13827	13031
8/4/2023	0.44	-67	332	328	1	332	1	0	0	14159	13359
8/11/2023	0.56	-64	(584)	(588)	1	0	0	(584)	(584)	13575	12771
8/18/2023	0.42	-77	0	0	0	0	0	0	0	13575	12771
8/25/2023	0.32	-49	19	(1)	5	876	3	(582)	(857)	13594	12770
9/1/2023	0.6	-18	448	444	1	448	1	0	0	14042	13214
9/8/2023	0.92	0	0	0	0	0	0	0	0	14042	13214
9/15/2023	0.92	0	267	263	1	267	1	0	0	14309	13477
9/22/2023	1.86	9	194	190	1	194	1	0	0	14503	13667
9/29/2023	1.45	86	0	0	0	0	0	0	0	14503	13667
10/6/2023	0.64	-64	690	678	3	938	2	(248)	(248)	15193	14345
10/13/2023	1.44	-16	(40)	(44)	1	0	0	(40)	(40)	15153	14301
10/20/2023	1.12	-1	(106)	(118)	3	213	1	(310)	(319)	15047	14183
10/27/2023	1.01	6	363	347	4	635	3	(272)	(272)	15410	14530
11/3/2023	1.27	59	341	325	4	341	4	0	0	15751	14855
11/10/2023	2.88	59	0	0	0	0	0	0	0	15751	14855
11/17/2023	2.9	64	0	0	0	0	0	0	0	15751	14855
11/24/2023	6	74	0	0	0	0	0	0	0	15751	14855
12/1/2023	2.55	89	0	0	0	0	0	0	0	15751	14855
12/8/2023	1.99	39	203	199	1	203	1	0	0	15954	15054
12/15/2023	1.83	-13	(152)	(160)	2	139	1	(291)	(291)	15802	14894
12/22/2023	0.67	-41	28	24	1	28	1	0	0	15830	14918
12/29/2023	0.54	0	0	0	0	0	0	0	0	15830	14918
1/5/2024	1.27	-41	291	287	1	291	1	0	0	16121	15205
1/12/2024	2.27	1	0	0	0	0	0	0	0	16121	15205
1/19/2024	2.87	87	0	0	0	0	0	0	0	16121	15205
1/26/2024	4.97	77	0	0	0	0	0	0	0	16121	15205
2/2/2024	3.15	65	0	0	0	0	0	0	0	16121	15205
2/9/2024	4.02	74	0	0	0	0	0	0	0	16121	15205
2/16/2024	3.46	88	0	0	0	0	0	0	0	16121	15205
2/23/2024	2.08	44	0	0	0	0	0	0	0	16121	15205
3/1/2024	2.15	1	0	0	0	0	0	0	0	16121	15205
3/8/2024	1.78	0	(187)	(203)	4	877	2	(889)	(889)	15934	15002

Date	In-samp pf	In-samp r2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
3/15/2024	0.84	43	248	244	1	248	1	0	0	16182	15246
3/22/2024	1.45	0	(127)	(139)	3	190	1	(191)	(191)	16055	15107
3/29/2024	1.26	-6	0	0	0	0	0	0	0	16055	15107
4/5/2024	0.97	-18	(687)	(711)	6	532	2	(693)	(1219)	15368	14396
4/12/2024	0.57	-76	247	243	1	247	1	0	0	15615	14639
4/19/2024	0.63	-55	(878)	(886)	2	85	1	(963)	(963)	14737	13753
4/26/2024	0.36	-61	116	96	5	780	3	(416)	(664)	14853	13849
5/3/2024	0.58	-49	(283)	(291)	2	88	1	(371)	(371)	14570	13558
5/10/2024	0.64	-33	(76)	(84)	2	107	1	(183)	(183)	14494	13474
5/17/2024	0.6	-41	0	0	0	0	0	0	0	14494	13474
5/24/2024	0.8	-56	(314)	(326)	3	247	2	(561)	(561)	14180	13148
5/31/2024	0.48	-52	0	0	0	0	0	0	0	14180	13148
6/7/2024	0.59	-64	38	26	3	497	1	(360)	(459)	14218	13174
6/14/2024	0.62	-40	(144)	(152)	2	0	0	(86)	(144)	14074	13022
6/21/2024	0.64	-6	7	3	1	7	1	0	0	14081	13025
6/28/2024	0.62	9	(301)	(313)	3	151	1	(365)	(452)	13780	12712
7/5/2024	0.62	6	280	276	1	280	1	0	0	14060	12988
7/12/2024	0.73	-20	(166)	(174)	2	15	1	(181)	(181)	13894	12814
7/19/2024	0.63	-36	206	198	2	446	1	(240)	(240)	14100	13012
7/26/2024	1.02	-22	497	481	4	797	2	(268)	(300)	14597	13493
8/2/2024	1.31	50	769	741	7	1730	4	(558)	(558)	15366	14234
8/9/2024	1.94	72	0	0	0	0	0	0	0	15366	14234
8/16/2024	1	0	821	809	3	1041	2	(220)	(220)	16187	15043
8/23/2024	1.15	-15	(1177)	(1189)	3	70	1	(1018)	(1247)	15010	13854
8/30/2024	0.75	-28	(656)	(676)	5	126	2	(625)	(782)	14354	13178
9/6/2024	0.63	-60	1149	1137	3	1403	2	(254)	(254)	15503	14315
9/13/2024	1.28	-25	1427	1415	3	1427	3	0	0	16930	15730
9/20/2024	1.56	3	(615)	(627)	3	189	1	(433)	(804)	16315	15103
9/27/2024	1.12	59	(84)	(92)	2	135	1	(219)	(219)	16231	15011
10/4/2024	1.53	78	0	0	0	0	0	0	0	16231	15011
10/11/2024	2.16	11	0	0	0	0	0	0	0	16231	15011
10/18/2024	0.73	3	36	20	4	217	1	(125)	(140)	16267	15031
10/25/2024	1.95	53	(58)	(66)	2	107	1	(165)	(165)	16209	14965
11/1/2024	1.19	73	0	0	0	0	0	0	0	16209	14965
11/8/2024	1.81	9	841	829	3	841	3	0	0	17050	15794
11/15/2024	2.49	34	0	0	0	0	0	0	0	17050	15794
11/22/2024	3.23	56	0	0	0	0	0	0	0	17050	15794
11/29/2024	4.7	86	0	0	0	0	0	0	0	17050	15794
12/6/2024	4.53	73	0	0	0	0	0	0	0	17050	15794
12/13/2024	3.95	53	0	0	0	0	0	0	0	17050	15794
12/20/2024	1.78	42	1383	1363	5	2200	3	(546)	(817)	18433	17157
12/27/2024	1.85	68	601	593	2	601	2	0	0	19034	17750
1/3/2025	2.67	79	0	0	0	0	0	0	0	19034	17750
1/10/2025	1.24	26	(43)	(67)	6	455	4	(345)	(345)	18991	17683
1/17/2025	1.2	-4	(326)	(342)	4	566	2	(679)	(892)	18665	17341
1/24/2025	0.61	-64	124	120	1	124	1	0	0	18789	17461
1/31/2025	0.56	-55	(334)	(354)	5	662	2	(648)	(996)	18455	17107
2/7/2025	0.59	0	(309)	(329)	5	598	2	(465)	(684)	18146	16778
2/14/2025	0.74	-24	666	654	3	666	3	0	0	18812	17432
2/21/2025	1.21	-26	(206)	(210)	1	0	0	(206)	(206)	18606	17222
2/28/2025	0.91	-23	236	212	6	694	3	(246)	(246)	18842	17434
3/7/2025	0.77	18	495	455	10	2662	5	(701)	(1214)	19337	17889
3/14/2025	1.33	57	1138	1114	6	1503	4	(249)	(279)	20475	19003
3/21/2025	1.64	70	487	467	5	873	4	(386)	(386)	20962	19470
3/28/2025	1.6	83	0	0	0	0	0	0	0	20962	19470
4/4/2025	2.07	85	0	0	0	0	0	0	0	20962	19470
4/11/2025	0.88	9	3732	3676	14	8716	9	(2911)	(3636)	24694	23146
4/18/2025	1.29	-10	(1123)	(1147)	6	152	1	(876)	(1230)	23571	21999
4/25/2025	1.05	1	1000	984	4	1657	3	(657)	(657)	24571	22983
5/2/2025	1.16	12	418	394	6	981	3	(312)	(563)	24989	23377
5/9/2025	1.22	43	528	512	4	679	3	(151)	(151)	25517	23889
5/16/2025	2.14	46	0	0	0	0	0	0	0	25517	23889

Date	In-samp pf	In-samp r2	osnp	NOnp$4	ont	ownp	ownt	ollt	odd	EQ	NetEq
5/23/2025	2.94	81	0	0	0	0	0	0	0	25517	23889
5/30/2025	1.83	69	100	88	3	472	1	(321)	(372)	25617	23977
6/6/2025	1.5	29	(566)	(574)	2	0	0	(490)	(566)	25051	23403
6/13/2025	0.8	-52	(489)	(497)	2	0	0	(327)	(489)	24562	22906
6/20/2025	0.19	-79	(527)	(535)	2	186	1	(713)	(713)	24035	22371
6/27/2025	0.26	-86	307	287	5	663	3	(203)	(203)	24342	22658
7/4/2025	0.34	-73	407	399	2	407	2	0	0	24749	23057
7/11/2025	0.59	-26	(31)	(35)	1	0	0	(31)	(31)	24718	23022
7/18/2025	0.79	0	(132)	(136)	1	0	0	(132)	(132)	24586	22886
7/25/2025	0.87	76	0	0	0	0	0	0	0	24586	22886
8/1/2025	2.28	36	0	0	0	0	0	0	0	24586	22886
8/8/2025	0.16	-90	(560)	(576)	4	393	2	(557)	(953)	24026	22310
8/15/2025	0.17	-94	(315)	(319)	1	0	0	(315)	(315)	23711	21991
8/22/2025	0.15	-93	58	46	3	265	1	(126)	(126)	23769	22037
8/29/2025	0.22	-85	102	98	1	102	1	0	0	23871	22135
9/5/2025	0.29	-77	(427)	(451)	6	376	2	(537)	(560)	23444	21684
9/12/2025	0.55	-36	44	36	2	118	1	(74)	(74)	23488	21720
9/19/2025	0.79	-39	1	(11)	3	80	2	(79)	(79)	23489	21709
9/26/2025	0.65	-44	(488)	(496)	2	0	0	(463)	(488)	23001	21213
10/3/2025	0.47	-61	62	54	2	284	1	(222)	(222)	23063	21267
10/10/2025	0.6	-66	1754	1742	3	1754	3	0	0	24817	23009
10/17/2025	2.83	8	0	0	0	0	0	0	0	24817	23009
10/24/2025	0.77	0	610	598	3	610	3	0	0	25427	23607
10/31/2025	0.94	-1	157	141	4	516	2	(303)	(359)	25584	23748
11/7/2025	1.12	-18	1000	976	6	1339	4	(291)	(291)	26584	24724
11/14/2025	1.26	0	917	905	3	917	3	0	0	27501	25629
11/21/2025	2.44	92	0	0	0	0	0	0	0	27501	25629
11/28/2025	1.4	9	1277	1265	3	1277	3	0	0	28778	26894
12/5/2025	1.66	12	93	85	2	93	2	0	0	28871	26979
12/12/2025	1.51	11	1101	1085	4	1101	4	0	0	29972	28064
12/19/2025	1.75	47	779	763	4	779	4	0	0	30751	28827
12/26/2025	4.07	95	0	0	0	0	0	0	0	30751	28827
1/2/2026	14.95	93	0	0	0	0	0	0	0	30751	28827
1/9/2026	2.31	71	0	0	0	0	0	0	0	30751	28827
1/16/2026	2.02	15	0	0	0	0	0	0	0	30751	28827
1/23/2026	0.29	-88	(163)	(187)	6	653	2	(477)	(706)	30588	28640
1/30/2026	0.33	-83	780	760	5	1091	4	(311)	(311)	31368	29400
2/6/2026	0.67	-49	978	950	7	1514	4	(409)	(536)	32346	30350
2/13/2026	1.19	35	(576)	(600)	6	864	3	(759)	(1198)	31770	29750
2/20/2026	1.14	52	(339)	(355)	4	359	3	(698)	(698)	31431	29395
2/27/2026	1.24	13	270	246	6	577	4	(222)	(307)	31701	29641
3/6/2026	1.41	-1	(84)	(116)	8	1093	3	(357)	(994)	31617	29525
3/13/2026	0.85	1	(684)	(708)	6	1231	2	(978)	(1358)	30933	28817
3/20/2026	0.87	4	175	155	5	657	2	(295)	(482)	31108	28972
3/27/2026	1	-32	(183)	(207)	6	733	2	(286)	(851)	30925	28765
4/3/2026	0.78	-62	1454	1438	4	2008	3	(554)	(554)	32379	30203
4/10/2026	0.95	-5	143	123	5	508	3	(195)	(242)	32522	30326

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

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

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

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 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:

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

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

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

ϕ_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 $\mathbf{n^{th}}$ 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** = $\mathbf{d^2P_F(T+1)/d^2t}$ 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.

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

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

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	9.3320
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.