Using The Goertzel Cycle Algorithm
To Trade The Russell 2000 5min Bars

With Walk Forward 5 days in-sample and 1 day out-of-sample

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

The Goertzel algorithm is not well known in the trading community but is used extensively in communications and frequency detection. As an example, we all are familiar with cellular phones. When you press a button have you ever wondered how the telephone company computers know what button you pushed? The answer is the Goertzel algorithm. This algorithm is built into tiny integrated circuits and immediately (within 43ms) detects the tone of the button you pushed.

In a previous working paper entitled "MESA vs Goertzel DFT", http://www.meyersanalytics.com/publications2/MesaVsGDFT.pdf we demonstrated that the Goertzel Algorithm(GZ), a subset of the Discrete Fourier Transform (DFT), has better frequency detection abilities of sine waves imbedded in noise than the MESA algorithm or the Fast Fourier transform when the noise amplitude is equal to or greater than the signal amplitude.

Given the better frequency detection of the GZ we will use the GZ here to find the cycle with the highest amplitude, also called the dominant cycle, to create a noise filtered signal curve that we will follow to create our strategy buy and sell signals.

The Goertzel Algorithm.

The value of the Discrete Fourier Transform is that for N input data points, the DFT can find the frequencies, amplitude and phases of the sine waves in the data at the discrete frequency points of 1/N, 2/N,…. to (N/2)/N. For instance if N, the number of price bars or closes, were equal to 20 we could find the amplitude and phases for the 20 period cycle (20 bars/ cycle), the 10 period cycle, the 6 2/3 period cycle all the way down to the 2 period cycle. As traders we are more accustomed to thinking of terms of periods like the 3 day cycle (frequency = 1/3 cycle/day) or the 10 bar cycle (frequency = 1/10 cycles/bar) etc. Unfortunately the DFT can only calculate equally spaced frequencies of 1/N. In the above example, where N=20, using the DFT we could only calculate the amplitudes of the periods (periods=1/frequency) of 20, 10, 6 2/3 etc. What if the true signal period was between 20 and 10? The DFT couldn't find it. That was the advantage of MESA. MESA was not constrained to the 1/N spacing. With MESA any grid of frequencies could be examined. As shown in my previous article, a special subset of the discrete Fourier transform called the Goertzel algorithm is also not constrained to 1/N spacing and can be used to find any frequency in between the 1/N frequency divisions.

Despite the advantage of the Goertzel algorithm frequency detection abilities, it has three drawbacks. One drawback of the Goertzel algorithm is that it is much slower than the Fast Fourier transform. If we had 512 data points and we wanted to look at 128 different frequencies, the FFT computation would be proportional to $512*\log_2(512)= 4608$ operations while the Goertzel computation would be proportional $512*128 = 65536$ operations. In other words, in this case, the Goertzel algorithm would take more than 10 times longer than the FFT to compute. However, as a computation time comparison, Goertzel would take about half the time as MESA to compute those 128 frequencies. The second drawback of the Goertzel algorithm is that in order to find a frequency in Goertzel when the noise amplitude is high you need enough data so that your lowest frequency (largest period) is able to complete at least 3 cycles. This means that if we were examining daily closing prices and we wanted to find periods of 75 days and less than we would need at least 3*75=225 days of prices in order to detect that period in noisy data. The third drawback of the Goertzel algorithm is that while it can detect the frequency within the 1/N spacing it cannot detect more than one frequency within that spacing. For instance if N=20, and we are looking for a frequency between 1/20 and 2/20, the Goertzel can detect the frequency anywhere at or between these two frequencies. However, if there were a second frequency in-between these two frequencies, Goertzel could not find it. If there were two frequencies between these two values, Goertzel would produce one frequency as a weighted average of the two. This is where MESA has a clear advantage. On data with a low noise component, Mesa could detect these two closely spaced frequencies. However, if the data is very noisy than MESA would not be able to detect the closely spaced frequencies either.

The Adaptive n Cycle Goertzel-DFT System.

The nature of intraday price movements is constantly changing due to current economic surprises, events and trader sentiment. Also the time of year changes the nature of intraday markets, such as the seasons, holidays, vacation time, etc. As such, the periods or frequencies found on intraday prices 3 weeks ago may no longer be the same as the frequencies found on today's intraday data. We would expect the frequencies found on intraday data to vary over time.

For this system we will create an indicator that walks forward one price bar at a time. The indicator will take a fixed number, N, of closing prices and use the Goertzel Algorithm (GZ) to find the frequency with the highest amplitude, also called the dominant cycle. Using that frequency, amplitude and phase, we will construct a new price that forecasts the price one bar ahead. We will save this next bar forecast value, or forecast point. Next we will move the N closing prices forward one bar adding the next bar and dropping the last bar so that we have exactly N closing prices again. With this new N closing prices window we compute the next bar forecast value and save it. We keep marching the N closing price window forward one bar at a time, calculate and save the new forecast point until we reach the end of our data. We will then connect all the generated forecast points to produce a curve that creates the next bar forecast as the dominant cycle used to create the next bar forecast changes slowly over time. Thus this curve adapts to the closing prices changing dominant cycle and projects one day ahead so that its lag is minimized as things change.

Adaptive Goertzel DFT System Construction Details

Unfortunately constructing the ***n*** cycle DFT of a price data series is not quite as simple as just taking N closing prices, and directly plugging them into a Goertzel algorithm.

The DFT assumes the time domain sample is periodic and repeats. Suppose a price series starts at 400 and wiggles and wags for 512 data samples ending at the value of 600. The DFT assumes that the price series starts at zero, suddenly jumps to 400, goes to 600 and suddenly jumps down to zero again and then repeats. The DFT must create all kinds of different frequencies in the frequency domain to try and match this type of behavior. These false frequencies created to match the jumps and the high average price completely swamp the amplitudes of any real frequencies making them look like noise. Fortunately this effect can be almost eliminated by a simple technique called end point flattening.

The calculation of end point flattening coefficients is simple. If x(1) represents the first price in the sampled data series, x(n) represent the last point in the data series and y(i) equal to the new endpoint flattened series then:

$$\mathbf{a = x(1) \quad b=(x(n)-x(1))/(n-1)}$$

$$\mathbf{y(i) = x(i) - [a+ b*(i-1)] \quad \text{for } i=1 \text{ to } n \quad (1)}$$

We can see that when i=1 then y(1)=0 and when i=n then y(n) =0. What we've done is subtract the beginning value of the time series to make the first value equal to zero and then rotate the rest of the time series such that the end point is now zero. This technique reduces the endpoint distortion but introduces a low frequency artifact into the Fourier Frequency spectrum. Fortunately we won't be looking for frequencies in that range so this distortion will have minimal impact.

n Cycle Goertzel-DFT Curve Construction

Before we start, we have to determine the largest period we will be looking to include in the ***n*** cycle Goertzel DFT construction. For intraday data the 3-day and 1 day cycles are very important. In this paper we will use 5-minute bars of the Russell 2000 Index Futures(TF). The TF trades on the Intercontinental Exchange (ICE) 22 hours a day. For our study we will only look at the US day trading session from 8:30am to 3:15pm CST Monday through Friday. Each day consists of 81 5min bars a day. Thus the 1-day cycle would need 81 bars. In order to detect the 1-day cycle we need the cycle to repeat at least three times. This means we need at least 3*81= 243 data points in order to detect the 1-day cycle using 5-minute bars. The 3-day cycle would need 3*81=243 bars. In order to detect the 3-day cycle using the Goertzel algorithm we need at least 3*243=729 5min bars. There is a small trick we can use to reduce the number of bars to calculate the 3 day cycle. If we had 15min bars then there would be 27 15min bars per day and three days of 15min bars would be 3*27=81 15min bars. For the GZ we would need to calculate the 3day cycle of 15min bars we would need 3*81=243 15min bars of prices. Now suppose for the TF 5min bar data we took every third bar back in time instead of every bar. That would be exactly the same as taking the close of 15min bars. We would still need 729 5min bars but we would only be using 243 of them. For the next GZ computation we would advance one 5min bar and only use every third bar in the past as before. This why it would be like computing the GZ for 3 days of 15min bars but on every 5min bar moving forward. We will use 256*3=768 five min bars with every third bar equal to 256 15min bars of TF data which will detect both the 3-day all cycles below 3 days.

We will use the Goertzel algorithm described in our previous article to determine the top frequency with the highest amplitudes. s. We will also use the Goertzel algorithm to determine the phase of the frequency with the highest amplitude.

Step 1 End flatten the 256 15min bars (every third bar of 5min prices) prices using equation (1) above.

Step 2 Use the Goertzel algorithm to calculate the amplitudes for the frequencies of 1/81(3 day 15min bar period) down to 1/4. Frequency = 1/period. We are scanning for periods because as traders we think in terms of periods not frequencies. That is, the 1 day cycle, the 20 bar cycle etc. Thus, here we are scanning for frequencies of 81 bars/cycle to 4 bars/cycle. The frequencies of 3 bars/cycle down to 2 bars/cycle move to fast with 15min bars to take advantage trading these cycles. The slippage and commissions would eat up any profits made.

Step 3 Find the frequency with the highest amplitudes, the dominant cycle, calculate the phase of this frequency and save these amplitude (a[i]), phase (phi[i]) and frequencies (f[i]). Where [i] is highest amplitudes found.

Step 4 Calculate the forecast next bar value and the end point bar value using the above frequency, amplitude and phase of the dominant cycle. The next bar forecast(fp) = a[i]*cos(2*PI*f[i]*(257 15min bars) +phi[i]) i=frequency number of highest amplitude and the Endpoint(ep) = a[i]*cos(2*PI*f[i]*256(15min bars) +phi[i]) where a[i]=amplitude, f[i]=frequency , phi[i]=phase of the frequency with the highest amplitude.

Step 5 Save the calculated forecast next bar point and the end point values. Call the forecast next point **fp(k)** and the end point **ep(k)** where k denotes the order of the sliding window. That is, the first sliding window k=1, the second, k=2, etc. Slide the 256 15min bars bar data window forward one 5min bar choosing every 3rd bar back, and repeat steps 1 through 4.

Why do we need **fp** and **ep**? When the data window is moved forward one bar at a time a new data sample is added to the end and the data sample at the beginning is subtracted. This adding and subtracting causes the end point flattening coefficients and the power in the frequency spectrum to jump around creating distortion and jitter in the calculation of the forecast next bar point. This random jumping as the data window slides forward in time adds a small random jump to the forecast next bar point curve. This jumping can be minimized by creating a curve from the two saved end points, **fp(k)** and **ep(k)**, above in step 5. Since turning points are of interest rather than magnitude then in **step 5** a new variable will be created called **sumv** where

sumv(k) = sumv(k-1) + fp(k)-ep(k)

fp(k)-ep(k) is like a one bar ahead momentum or velocity. This new curve **sumv(k)** is the sum of all the changes in the next bar's ***n*** cycle forecast value fp(k) from the end point n cycle value. This change series minimizes the magnitude jump problem creating a fairly smooth momentum sum curve.

The Adaptive *n* Cycle Goertzel-DFT System Defined

Even though **sumv** is a fairly smooth curve it still has a number of short term wiggles preventing us from simply going long when the curve turns up and going short when the curve turns down. To create a system, we will use a simple curve following technique on TF 5-minute bars.

Buy Rule:

- **IF sumv** has moved up by more than the point amount of *pntup* from the lowest low recorded in **sumv** while short then buy the ***TF*** futures at the market..

Sell Rule:

- **IF sumv** has moved down by more than the point amount *pntdn* from the highest high recorded in **sumv** while long then sell the ***TF*** futures at the market.

Intraday Bars Exit Rule:

Close the position at 1500 CST (no trades will be carried overnight).

Testing The Adaptive N Cycle Goertzel-DFT (GZ) System Using Walk Forward Optimization

There will be three strategy parameters to determine:

1. ***ncy***, Number of Cycles (for this study we will only look at 1(the dominant cycle).
2. ***pup***, if **sumv** has moved up by more than the point amount of *pup* from the lowest low recorded in **sumv** while short then issue a buy signal
3. ***pdn***, if **sumv** has moved down by more than the point amount *pdn* from the highest high recorded in **sumv** while long then sell

As mentioned, to test this system we will use five minute bar prices of the mini Russell 2000 index futures contract traded on the Intercontinental Exchange (ICE) and known by the symbol TF for the 494 trading days from April 1 2017 to April 7 2017. Note that the TF price multiplier changed from $100 to $50 per index point on December 5, 2016.

We will test the GZ strategy with the above TF 5 min bars on a ***walk forward basis***, where the in-sample(IS) will be 5 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 (TSMC) optimization on many different strategy inputs, TSMC 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 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 can't 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 with no out-of-sample testing cause loses when traded in real time from something that looked great in the in-sample section.

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

Finding The GZ Strategy Parameters Using Walk Forward Optimization
There are two strategy parameters to find, *pntup and pntdn.*

For the test data we will run the TS or MC optimization engine on **TF** 5 min price bars(using every third bar) from 4/1/2015 to 4/7/2017 with the following optimization ranges for the GZ strategy inputs. This will create **494, 5 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 4day IS. All other ***IS*** periods consist of 5 trading weekdays.
The optimization ranges are:

1. **ncy= 1**
2. **pup from 0.2 to 6 steps of 0.2**
3. **pdn from 0.2 to 6 in steps of 0.2**
4. trh = 0 not used
5. iepflat = 1
6. tstart=0.375
7. logofcls=0
8. nsamp = 256 number of bars for GZ computation
9. nX= 3 chooses every 3rd 5min bar
10. myStartTime = 830
11. Xopn = 0
12. Xtime = 1500
13. XonCls =0
14. xmult = 1
15. prc = c

The above pntup and pntdn ranges will produce 900 different input combinations or cases of the strategy input parameters for each of the 494 in-sample/out-of-sample files for the 16 months of 5 min bar TF data.

The question we are attempting to answer statistically is which best performance metric or combination of best performance metrics (which we call a ***filter***) applied to the in-sample section will produce in-sample strategy inputs that produce statistically valid profits in the out-of-sample section. In other words we wish to find a performance metric ***filter*** that we can apply to the in-sample section that can give us strategy inputs that will produce, on average, good trading results in the future.

When TS or MC does an optimization routine over many combinations of inputs, it creates output page that has as its rows each strategy input combination and as it's columns various trading performance measures such as Profit Factor, Total Net Profits, etc. An example of a simple filter would be to choose the strategy input optimization row in the in-sample section that had the highest Net Profit or perhaps a row that had the best Profit Factor with their associated strategy inputs. Unfortunately it was found that this type of simple metric performance filter very rarely produces good out-of-sample results. More complicated metric filters can produce good out-of-sample results minimizing spurious price movement biases in the selection of strategy inputs.

Here is a combination ***filter*** that is used in this paper with good out-of-sample results. **R2** is the in-sample trade equity regression trend line coefficient of correlation $\mathbf{r^2}$. $\mathbf{r^2}$ is a measure of how well a straight line fits the equity curve generated by a set of in-sample strategy inputs. High **r2** values in the in-sample section usually mean poor performance in the out-of-sample-section. This is a kind of reversion to the mean and a measure of how well the price noise is being fitted in the IS section. So, in the in-sample section we eliminate all strategy input rows that have a **r2>80**. In addition, we wish to limit the number losing trades in a row in the 5 day IS period to 2 or less (**lr<2**). The PWFO generates the metric **std.** This metric is the in-sample **std**= standard deviation of IS trades. Let us choose the 10 rows that contain the smallest **std** values from the rows that are left from the **lr-r2** elimination. This particular filter will now leave 10 cases or rows in the in-sample section that satisfy the above filter conditions. . Suppose for this filter, within the 10 in-sample rows that are left, we want the row that has the maximum PWFO metric wr in the in-sample section**. Wr is the maximum consecutive winning trades in a row**. This would produce a filter named **b10std|lr<2r2<80-wr.** This in-sample filter leaves only one row in the PWFO in-sample section with its associated strategy inputs and out-of-sample net profit in the out-of-sample section. The **b10std|lr<2r2<80-wr** filter finds the strategy inputs parameters in each of the 494 in-sample sections and applies these inputs to the out-of-sample section. Using the filter in-sample strategy inputs on the 494 out-of-sample sections, the average out-of-sample performance is calculated. In addition many other important out-of-sample performance statistics for this filter are calculated and summarized. **Figure 3** shows such a filter computer run along with a small sample of other filter combinations that are constructed in a similar manner. **Row 3** of the sample output in **Figure 3** shows the results of the filter discussed above. Commissions and slippage for the new TF mini were estimated at $12 round trip for one contract. A total of 11532 different metric filters were examined. More on this below on how that number of filters combinations effect the probability that the filter chosen was or was not due to chance.

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 494 out-of-sample files of $**15.7** with a bootstrap standard deviation of **$14.8**. (Side Note. The average is the average per out-of-sample period. So, the average for the random selection would be the random toNP/494 and the average for the filter would be the filter toNP/# of OOS periods traded or 36249/488=74.28). The probability of obtaining our filters average daily net profit **of 74.28 (36249/488)** is $\mathbf{3.85x10^{-5}}$ which is **3.96** standard deviations from the bootstrap average. For our filter, in row 3 in Figure 3, the expected number of cases that we could obtain by pure chance that would match or exceed **$74.28** is
$[1\text{-}(1\text{-}\ \mathbf{3.85\ 10^{-5}})^{11532}]$**~** **11532**x $\mathbf{3.85\ 10^{-5}}$ = **0.44** where **11532** is the total number of different filters we looked at in this run. This number is less than one so it is improbable that our result was due to pure chance.

Results

Figure 1 presents a graph of the equity curve generated by using the filter on the 494 days ending 4/21/15 to 4/7/17 (note the starting date 4/21/15 was part of the first 5 day in-sample period plus the number of MaxBarsBack (256*3=758 5min bars ~10 trading days) and the OOS weekday after the 5 trade day in-sample was 4/21/15. The equity curves is 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 TF Daily Closing prices superimposed on the Equity Chart.

Figure 2 presents a plot of the GZ Strategy buy/sells and the GZ Indicator on the TF 5min bars for 3/21/2017 - 3/30/2017.

Table 1 below presents a table of the 494 in-sample and out-of-sample windows, the **Filter** selected in-sample strategy inputs and the daily out-of-sample profit/loss results using the filter described above.

Discussion of Strategy Performance
In Figure 3, Row 3 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 62 days for this filter. This means that 62 trading days was the longest time that the equity for this strategy failed to make a new equity high. %Wtr is the percentage of all OOS trades that were wins or positive. For this filter, the %Wtr=54%, %P=% winning oos days =59% and the average oos winning trade to the average oos losing trade ratio(oW|oL) was 1.3. wpr=14 is the maximum number of consecutive winning oos periods(days) in a row and lpr=7 is the maximum number of consecutive losing oos periods(days) in a row. The Largest losing trade in the whole period was ($1150) and the largest losing day was ($1950).

To see the effect of walk forward analysis, take a look at **Table 1**. Notice how the input parameters ***ncy, pntup, pntdn*** take sudden jumps from high to low and back . This is the walk forward process quickly adapting to changing volatility conditions in the in-sample sample.

In Figure 1, which presents a graph of the equity curve using the filter on the 494 trading days of out-of-sample data, notice how the equity curve follows the 2nd order polynomial trend line with an R^2 of 0.97. This R^2 only dropped to 0.96 for the net equity curve. In addition the sharp 21% drop of TF in January/February 2016 produced a $5900 gain in the equity. Further big drops of TF in June 2016 and October 2016 did not produce losses or gains in equity. In comparing the equity curve to TF price moves, both up and down, the GZ strategy handled both up and down moves of TF with relatively smooth and consistent up trending equity curve profits.

Using this filter, the strategy was able to generate $36,249 net equity after commissions and slippage of $12 trading one TF contract for 494 days. This period of time from 4/21/15 to 4/7/17 was a volatile market. Yet the GZ strategy was able to adapt quite well. From Figure 3 and Table 1, the largest losing OOS trade was -$1150 and the largest losing day was -$1950 on 7/7/15. The largest drawdown was -$3815 from 6/17/15 to 7/8/15 and -$3630 from 7/5/16 to 9/13/16. Both recovered to new equity highs in 14 trading days.

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 4 trades/day with an average of 1.6 trades/day with a medium of 1 trade/day. For the no trade days, the inputs found by the filter in the in-sample section generated no trades in the out-of-sample section or there were no cases in the in-sample section that fit thee filter.

Given 23 hour trading of the TS, restricting the strategy to trade only from 830am to 3:00pm CT caused the strategy to miss many profitable trends opportunities when Asia and then Europe opened trading in the early morning. Further research will include the A.M. time zones.

References:

1. Burg, J. P., 'Maximum Entropy Spectral Analysis", Ph.D. dissertation, Stanford University, Stanford, CA. May 1975.
2. Goertzel, G., "An Algorithm for the evaluation of finite trigonometric series" American Math Month, Vol 65, 1958 pp34-35.
3. Kay, Steven M., "Modern Spectral Estimation", Prentice Hall, 1988
4. Marple, Lawrence S. Jr., "Digital Spectral Analysis With Applications", Prentice Hall, 1987
5. Meyers, Dennis , "MESA vs Goertzel DFT", *Working Paper,* http://meyersanalytics.com/articles.htm
6. Press, William H., et al, "Numerical Receipts in C++: the Art of Scientific Computing", Cambridge Press, 2002.
7. Oppenheim, A, Schafer, R. and Buck, J., "Discrete Time Signal Processing", Prentice Hall, 1996, pp663-634
8. Proakis, J. and Manolakis, D. "Digital Signal Processing-Principles, Algorithms and Applications", Prentice Hall, 1996., pp480-481

Figure 1 Graph of GZ Strategy Equity Applying the Walk Forward Filter Each Day on the in-sample section On TF 5min Bar Prices 4/21/2015 to 4/7/2017

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 TF Daily Closing prices superimposed on the Equity Chart.

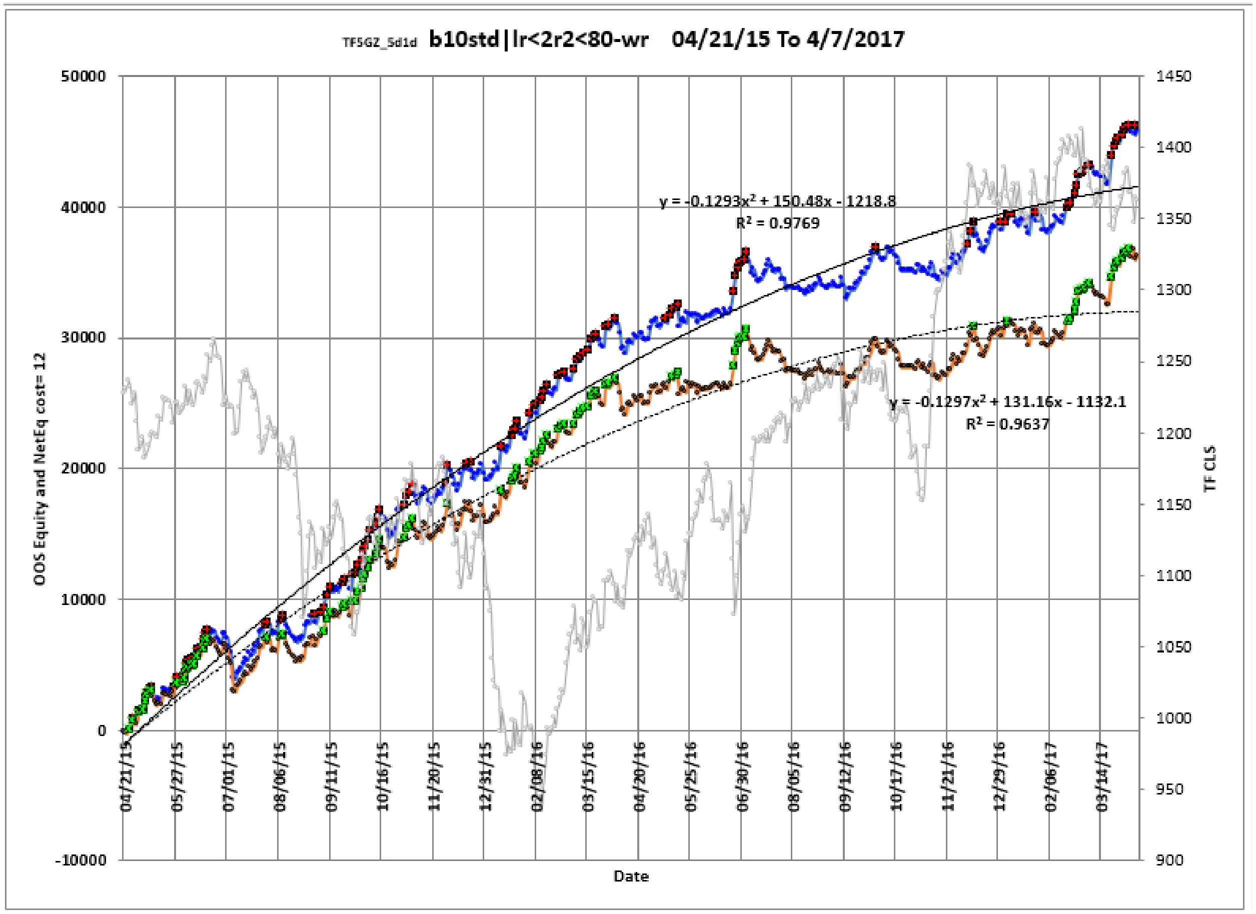

Figure 2 TF GZ Strategy 5-minute bar chart from 3/21/17-3/30/17

Figure 3 Partial output of the Walk Forward Metric Performance Explorer (WFME)

1	TF5GZ-5d1d	s04/21/15	e04/07/17	#494	AnyTnp					a15.7	s14.8	f11532								c=$12				
2	Filter-Metric	toGP	toNP	aoGP	aoTr	ao#T	oW|oL	%Wtr	%P	t	std	LLtr	LLp	eqDD	wpr	lpr	#	eqTrn	eqV^2	eqR2	Dev^2	Blw	BE	Prob
3	b10std|lr<2r2<80-wr	45825	36249	94	57.4	1.6	1.3	54	58	4.25	488	-1150	-1950	-3815	14	7	488	86	23	94	3044	62	108	3.85E-05
4	b10std|lr<2r2<80-m(ru-p)	45670	36154	94	57.6	1.6	1.26	54	57	4.18	494	-1150	-1950	-5360	10	9	488	86	-9	89	4264	108	112	4.07E-05
5	b10std|lr<2r2<80-t	44760	35268	92	56.6	1.6	1.3	53	56	4.09	497	-1150	-1950	-3980	11	7	487	82	36	95	2818	107	117	6.47E-05
6	b10std|lr<2r2<90-wr	44945	35225	92	55.5	1.7	1.36	52	57	4.07	500	-1150	-1950	-4035	11	7	488	88	39	95	2917	103	118	6.90E-05
7	b10std|lr<2r2<80-e-3	44415	34983	91	56.5	1.6	1.3	53	56	4.08	494	-1150	-1950	-6430	11	9	486	80	-19	87	4486	160	117	7.29E-05
8	b10std|lr<2r2<80-%P	44360	34832	91	55.9	1.6	1.33	53	56	4.06	496	-1150	-1950	-4745	10	7	487	83	37	95	2795	105	118	8.26E-05
9	b10std|lr<3r2<80-e-3	44050	34414	90	54.9	1.6	1.31	53	55	3.96	501	-1150	-1950	-5445	11	9	492	79	-2	90	3767	98	125	1.26E-04
10	b10std|lr<3r2<80-%P	43740	34140	89	54.7	1.6	1.34	52	56	3.95	500	-1200	-1950	-3400	10	7	491	81	53	97	2008	46	126	1.40E-04
11	b10std|lr<3r2<80-mTrd	43390	33874	88	54.7	1.6	1.3	53	55	3.96	494	-1150	-1950	-3775	13	9	491	84	55	96	2293	60	125	1.62E-04

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

Row 1 TF5GZ-5d1d is the PWFO output files abbreviation, First OOS Day End Date(4/21/15), Last OOS Day End Date(4/7/17), **Number of days**(#494) **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=$12).

Filter = The filter that was run. Row 3 filter **b10std|lr<2r2<80-wr**

b10std|lr<2r2<80-wr filter produced the following average 494 day statistics on row 3.

toGP = Total out-of-sample(oos) Gross profit for these 494 days.

toNP = Total oos gross profit(toGP) minus the total trade cost.
toNP=toGP – (Number of trade days)*ao#T*Cost.

aoGP = Average 1 day oos gross profit for the 494 days

aoTr = Average oos trade profit

ao#T = Average number of oos trades per day

oW|oL the ratio of the average winning oos trades to average losing oos trades.

%Wtr = The percentage of oos trades that were profitable

%P = The percentage of oos days that were profitable

t = The student t statistic for the 494 daily oos profits. The higher the t statistic the higher the probability that this result was not due to pure chance

std = The standard deviation of the 494 daily oos profits

LLtr = The largest losing oos trade in the whole period

LLp = The largest losing oos period(day)

eqDD = The oos equity drawdown

wpr = The largest number of consecutive winning oos days in a row

lpr = The largest number of consecutive losing oos days in a row

\# = The number of days this filter produced a daily result. Note for some days there can be no strategy inputs that satisfy the filter's criteria.

eqTrn = The straight line trend of the oos gross profit equity curve in $/day.

eqV^2 = The ending velocity of 2^{nd} order polynomial that is fit to the equity curve

eqR2 = The correlation coefficient(r^2) of a straight line fit to the equity curve

Dev^2 = A measure of equity curve smoothness. The square root of the average [(equity curve minus a straight line)^2]

Blw = The maximum number of days the oos equity curve failed to make a new high.

BE = Break even days. Assuming the average and standard deviation are from a normal distribution, this is the number of days you would have to trade to have a 98% probability that your oos equity is above zero.

Prob = the probability that the filter's daily average toNP = toNP/(# =number of filter trading days) was due to pure chance.

Table 1 Walk Forward Out-Of-Sample Performance Summary for the TF 5-min Goertzel Strategy

TF-5 min bars 4/21/2014 - 4/7/2017. The input values *ncy, pup, pdn* are the values found from applying the filter to the in-sample section optimization runs.

Filter: b10std|lr<2r2<80-wr LR<=2, r2<80 then bottom 10 std, then row with the maximum wr

osnp = Weekly Out-of-sample net profit from strategy inputs chosen by In-sample Section filter
ont = The number of trades in the out-of-sample week from strategy inputs chosen by In-sample Section filter.
NetOsnp = osnp-ont*$12
Equity = running sum of the weekly out-of-sample profits(Osnp)
NetEq = running sum of weekly out-of-sample profits minus $25*Ont
Note: Blank rows indicate that no out-of-sample trades were made that week

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
04/14/15	to	04/20/15	04/21/15	(135)	2	(135)	(159)	(159)	1	0.8	5.4	3	830	1500	1227.9
04/15/15	to	04/21/15	04/22/15	(110)	1	(245)	(122)	(281)	1	1.6	5	3	830	1500	1231
04/16/15	to	04/22/15	04/23/15	340	1	95	328	47	1	0.4	5	3	830	1500	1236.1
04/17/15	to	04/23/15	04/24/15	(65)	2	30	(89)	(42)	1	1.6	5.4	3	830	1500	1232.1
04/20/15	to	04/24/15	04/27/15	910	1	940	898	856	1	5.8	5.4	3	830	1500	1219.4
04/21/15	to	04/27/15	04/28/15	(185)	2	755	(209)	647	1	0.4	2.2	3	830	1500	1226.9
04/22/15	to	04/28/15	04/29/15	(215)	2	540	(239)	408	1	0.6	3	3	830	1500	1208
04/23/15	to	04/29/15	04/30/15	1045	1	1585	1033	1441	1	1	3.4	3	830	1500	1187.5
04/24/15	to	04/30/15	05/01/15	65	2	1650	41	1482	1	4.8	3.8	3	830	1500	1192.3
04/27/15	to	05/01/15	05/04/15	70	1	1720	58	1540	1	2	3.6	3	830	1500	1196.1
04/28/15	to	05/04/15	05/05/15	795	1	2515	783	2323	1	5.8	0.2	3	830	1500	1182.1
04/29/15	to	05/05/15	05/06/15	410	2	2925	386	2709	1	2.4	2.2	3	830	1500	1185.7
04/30/15	to	05/06/15	05/07/15	315	1	3240	303	3012	1	5.2	0.6	3	830	1500	1191.4
05/01/15	to	05/07/15	05/08/15	75	2	3315	51	3063	1	4.2	0.8	3	830	1500	1197.4
05/04/15	to	05/08/15	05/11/15	(490)	2	2825	(514)	2549	1	3	1.6	3	830	1500	1199.3
05/05/15	to	05/11/15	05/12/15	(385)	1	2440	(397)	2152	1	3.4	0.8	3	830	1500	1199
05/06/15	to	05/12/15	05/13/15	(290)	1	2150	(302)	1850	1	0.2	4.2	3	830	1500	1196.7
05/07/15	to	05/13/15	05/14/15	215	1	2365	203	2053	1	4.8	5.2	3	830	1500	1210.6
05/08/15	to	05/14/15	05/15/15	(105)	2	2260	(129)	1924	1	4.8	5.2	3	830	1500	1208.8
05/11/15	to	05/15/15	05/18/15	835	1	3095	823	2747	1	4.8	5	3	830	1500	1223.7
05/12/15	to	05/18/15	05/19/15	(15)	1	3080	(27)	2720	1	2.8	0.6	3	830	1500	1222.4
05/13/15	to	05/19/15	05/20/15	(140)	1	2940	(152)	2568	1	1	0.6	3	830	1500	1223.2
05/14/15	to	05/20/15	05/21/15	60	1	3000	48	2616	1	0.2	0.6	3	830	1500	1221.4
05/15/15	to	05/21/15	05/22/15	(35)	2	2965	(59)	2557	1	0.2	2	3	830	1500	1217.1
05/19/15	to	05/25/15	05/26/15	360	1	3325	348	2905	1	5.8	4.8	3	830	1500	1206.5
05/20/15	to	05/26/15	05/27/15	760	1	4085	748	3653	1	2.4	6	3	830	1500	1220.6
05/21/15	to	05/27/15	05/28/15	(345)	2	3740	(369)	3284	1	2.6	1.8	3	830	1500	1220.8
05/22/15	to	05/28/15	05/29/15	280	1	4020	268	3552	1	5.8	6	3	830	1500	1213
05/25/15	to	05/29/15	06/01/15	150	1	4170	138	3690	1	6	6	3	830	1500	1216.4
05/26/15	to	06/01/15	06/02/15	330	1	4500	318	4008	1	5.4	4.8	3	830	1500	1218
05/27/15	to	06/02/15	06/03/15	635	1	5135	623	4631	1	5.4	4.6	3	830	1500	1232.2
05/28/15	to	06/03/15	06/04/15	220	2	5355	196	4827	1	0.4	0.8	3	830	1500	1219.9
05/29/15	to	06/04/15	06/05/15	145	2	5500	121	4948	1	0.4	1	3	830	1500	1228
06/01/15	to	06/05/15	06/08/15	50	2	5550	26	4974	1	0.4	0.6	3	830	1500	1220.3
06/02/15	to	06/08/15	06/09/15	105	2	5655	81	5055	1	0.2	1	3	830	1500	1218.7
06/03/15	to	06/09/15	06/10/15	630	2	6285	606	5661	1	0.2	0.6	3	830	1500	1234.5
06/04/15	to	06/10/15	06/11/15	(45)	1	6240	(57)	5604	1	0.2	0.8	3	830	1500	1235.1
06/05/15	to	06/11/15	06/12/15	80	2	6320	56	5660	1	2	3.6	3	830	1500	1232.8
06/08/15	to	06/12/15	06/15/15	630	1	6950	618	6278	1	4.8	3.6	3	830	1500	1227.6
06/09/15	to	06/15/15	06/16/15	500	1	7450	488	6766	1	4.2	1.6	3	830	1500	1238.1
06/10/15	to	06/16/15	06/17/15	260	1	7710	248	7014	1	4.4	1.6	3	830	1500	1235
06/11/15	to	06/17/15	06/18/15	(480)	2	7230	(504)	6510	1	4.4	1.6	3	830	1500	1253.7
06/12/15	to	06/18/15	06/19/15	70	2	7300	46	6556	1	0.2	0.2	3	830	1500	1250

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
06/15/15	to	06/19/15	06/22/15	340	2	7640	316	6872	1	0.2	1.6	3	830	1500	1260.8
06/16/15	to	06/22/15	06/23/15	(145)	2	7495	(169)	6703	1	0.2	1.4	3	830	1500	1264.6
06/17/15	to	06/23/15	06/24/15	(475)	2	7020	(499)	6204	1	0.2	1.8	3	830	1500	1253.3
06/18/15	to	06/24/15	06/25/15	(150)	2	6870	(174)	6030	1	0.6	0.4	3	830	1500	1253
06/19/15	to	06/25/15	06/26/15	(235)	1	6635	(247)	5783	1	3	6	3	830	1500	1252.2
06/22/15	to	06/26/15	06/29/15	665	1	7300	653	6436	1	4.6	6	3	830	1500	1218
06/23/15	to	06/29/15	06/30/15	30	2	7330	6	6442	1	3.4	3.6	3	830	1500	1221.9
06/24/15	to	06/30/15	07/01/15	(305)	1	7025	(317)	6125	1	3.4	3.6	3	830	1500	1224.5
06/25/15	to	07/01/15	07/02/15	(705)	2	6320	(729)	5396	1	3.4	2.8	3	830	1500	1217.1
06/29/15	to	07/03/15	07/06/15	(385)	2	5935	(409)	4987	1	4.4	5.6	3	830	1500	1218.9
06/30/15	to	07/06/15	07/07/15	(1950)	2	3985	(1974)	3013	1	3.8	0.4	3	830	1500	1217.6
07/01/15	to	07/07/15	07/08/15	(90)	1	3895	(102)	2911	1	6	5.8	3	830	1500	1198.5
07/02/15	to	07/08/15	07/09/15	435	2	4330	411	3322	1	5.6	5.8	3	830	1500	1200.6
07/03/15	to	07/09/15	07/10/15	130	1	4460	118	3440	1	3.4	3	3	830	1500	1217.3
07/06/15	to	07/10/15	07/13/15	240	1	4700	228	3668	1	3.8	3	3	830	1500	1235
07/07/15	to	07/13/15	07/14/15	395	1	5095	383	4051	1	5.2	5.2	3	830	1500	1241.3
07/08/15	to	07/14/15	07/15/15	265	1	5360	253	4304	1	2.8	2.8	3	830	1500	1236.4
07/09/15	to	07/15/15	07/16/15	(40)	2	5320	(64)	4240	1	1	3.2	3	830	1500	1243
07/10/15	to	07/16/15	07/17/15	550	2	5870	526	4766	1	0.6	3.4	3	830	1500	1236.2
07/13/15	to	07/17/15	07/20/15	(185)	2	5685	(209)	4557	1	0.2	5	3	830	1500	1231
07/14/15	to	07/20/15	07/21/15	270	2	5955	246	4803	1	1	3.2	3	830	1500	1224.1
07/15/15	to	07/21/15	07/22/15	435	1	6390	423	5226	1	2.4	2.2	3	830	1500	1229
07/16/15	to	07/22/15	07/23/15	220	1	6610	208	5434	1	5	5.6	3	830	1500	1214.9
07/17/15	to	07/23/15	07/24/15	795	1	7405	783	6217	1	5	5.6	3	830	1500	1196.8
07/20/15	to	07/24/15	07/27/15	130	2	7535	106	6323	1	1.2	2	3	830	1500	1184.8
07/21/15	to	07/27/15	07/28/15	515	1	8050	503	6826	1	1.4	2	3	830	1500	1193.3
07/22/15	to	07/28/15	07/29/15	275	2	8325	251	7077	1	1	2	3	830	1500	1196.8
07/23/15	to	07/29/15	07/30/15	(425)	1	7900	(437)	6640	1	4.2	2.6	3	830	1500	1202.5
07/24/15	to	07/30/15	07/31/15	240	1	8140	228	6868	1	1.4	4	3	830	1500	1209.6
07/27/15	to	07/31/15	08/03/15	(825)	2	7315	(849)	6019	1	2.8	4.2	3	830	1500	1202.3
07/28/15	to	08/03/15	08/04/15	185	1	7500	173	6192	1	3	1.2	3	830	1500	1196.6
07/29/15	to	08/04/15	08/05/15	(195)	2	7305	(219)	5973	1	1.2	1.2	3	830	1500	1202
07/30/15	to	08/05/15	08/06/15	895	1	8200	883	6856	1	1.2	0.8	3	830	1500	1184.6
07/31/15	to	08/06/15	08/07/15	330	2	8530	306	7162	1	3.6	6	3	830	1500	1176.3
08/03/15	to	08/07/15	08/10/15	225	1	8755	213	7375	1	6	5.8	3	830	1500	1191.4
08/04/15	to	08/10/15	08/11/15	(320)	2	8435	(344)	7031	1	5.8	5.4	3	830	1500	1181.3
08/05/15	to	08/11/15	08/12/15	(475)	1	7960	(487)	6544	1	6	3.8	3	830	1500	1178.7
08/06/15	to	08/12/15	08/13/15	(310)	1	7650	(322)	6222	1	0.2	3.6	3	830	1500	1173.9
08/07/15	to	08/13/15	08/14/15	(325)	2	7325	(349)	5873	1	1.4	0.2	3	830	1500	1183.2
08/10/15	to	08/14/15	08/17/15	(165)	2	7160	(189)	5684	1	1.4	3	3	830	1500	1195.3
08/11/15	to	08/17/15	08/18/15	(150)	2	7010	(174)	5510	1	1	3.8	3	830	1500	1184.3
08/12/15	to	08/18/15	08/19/15	(275)	2	6735	(299)	5211	1	0.6	3	3	830	1500	1170
08/13/15	to	08/19/15	08/20/15	265	2	7000	241	5452	1	0.4	2.4	3	830	1500	1139.5
08/14/15	to	08/20/15	08/21/15	(195)	2	6805	(219)	5233	1	5	4.8	3	830	1500	1128.5
08/17/15	to	08/21/15	08/24/15	305	1	7110	293	5526	1	5	5.8	3	830	1500	1069.9
08/18/15	to	08/24/15	08/25/15	835	3	7945	799	6325	1	5.2	0.8	3	830	1500	1084
08/19/15	to	08/25/15	08/26/15	210	3	8155	174	6499	1	5.2	0.8	3	830	1500	1102.4
08/20/15	to	08/26/15	08/27/15	(15)	2	8140	(39)	6460	1	3	2.8	3	830	1500	1126.1
08/21/15	to	08/27/15	08/28/15	545	1	8685	533	6993	1	3	4	3	830	1500	1136.5
08/24/15	to	08/28/15	08/31/15	200	3	8885	164	7157	1	2.2	2.8	3	830	1500	1128.5
08/25/15	to	08/31/15	09/01/15	(725)	1	8160	(737)	6420	1	1.6	2.8	3	830	1500	1104.3
08/26/15	to	09/01/15	09/02/15	470	1	8630	458	6878	1	5.6	4.8	3	830	1500	1118.1
08/27/15	to	09/02/15	09/03/15	355	2	8985	331	7209	1	2.4	1.8	3	830	1500	1115.8
08/28/15	to	09/03/15	09/04/15	(65)	1	8920	(77)	7132	1	2.6	1.8	3	830	1500	1108.9
09/01/15	to	09/07/15	09/08/15	485	2	9405	461	7593	1	5	1.8	3	830	1500	1132
09/02/15	to	09/08/15	09/09/15	995	1	10400	983	8576	1	0.6	1.6	3	830	1500	1121.1
09/03/15	to	09/09/15	09/10/15	(80)	2	10320	(104)	8472	1	2.4	3.6	3	830	1500	1124.2
09/04/15	to	09/10/15	09/11/15	625	1	10945	613	9085	1	2.4	4.2	3	830	1500	1133.1

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
09/07/15	to	09/11/15	09/14/15	(410)	2	10535	(434)	8651	1	2.4	3	3	830	1500	1125.4
09/08/15	to	09/14/15	09/15/15	30	2	10565	6	8657	1	2.8	3.8	3	830	1500	1139.7
09/09/15	to	09/15/15	09/16/15	330	1	10895	318	8975	1	3.6	4.2	3	830	1500	1149.1
09/10/15	to	09/16/15	09/17/15	(295)	1	10600	(307)	8668	1	5.6	1.4	3	830	1500	1150.6
09/11/15	to	09/17/15	09/18/15	265	1	10865	253	8921	1	5.6	1.4	3	830	1500	1140.5
09/14/15	to	09/18/15	09/21/15	475	1	11340	463	9384	1	3.2	4.2	3	830	1500	1138.9
09/15/15	to	09/21/15	09/22/15	210	1	11550	198	9582	1	2.6	3.8	3	830	1500	1118
09/16/15	to	09/22/15	09/23/15	(155)	2	11395	(179)	9403	1	3.6	3.8	3	830	1500	1112.8
09/17/15	to	09/23/15	09/24/15	(145)	2	11250	(169)	9234	1	6	4.8	3	830	1500	1111.6
09/18/15	to	09/24/15	09/25/15	(575)	2	10675	(599)	8635	1	5.8	4.4	3	830	1500	1093.8
09/21/15	to	09/25/15	09/28/15	1215	1	11890	1203	9838	1	5.8	3.6	3	830	1500	1063.7
09/22/15	to	09/28/15	09/29/15	120	2	12010	96	9934	1	0.4	1.6	3	830	1500	1057.6
09/23/15	to	09/29/15	09/30/15	700	2	12710	676	10610	1	0.6	1.8	3	830	1500	1073.7
09/24/15	to	09/30/15	10/01/15	(930)	3	11780	(966)	9644	1	0.2	0.6	3	830	1500	1073.2
09/25/15	to	10/01/15	10/02/15	1240	3	13020	1204	10848	1	0.2	0.4	3	830	1500	1091.4
09/28/15	to	10/02/15	10/05/15	790	1	13810	778	11626	1	0.4	0.4	3	830	1500	1114.5
09/29/15	to	10/05/15	10/06/15	345	1	14155	333	11959	1	0.2	0.4	3	830	1500	1106.2
09/30/15	to	10/06/15	10/07/15	495	2	14650	471	12430	1	0.2	0.2	3	830	1500	1128.1
10/01/15	to	10/07/15	10/08/15	655	1	15305	643	13073	1	0.2	0.8	3	830	1500	1138.6
10/02/15	to	10/08/15	10/09/15	(210)	2	15095	(234)	12839	1	1.4	3	3	830	1500	1139.4
10/05/15	to	10/09/15	10/12/15	20	1	15115	8	12847	1	4.8	0.6	3	830	1500	1140
10/06/15	to	10/12/15	10/13/15	640	1	15755	628	13475	1	5	3.8	3	830	1500	1121.7
10/07/15	to	10/13/15	10/14/15	580	1	16335	568	14043	1	1.2	1.4	3	830	1500	1110
10/08/15	to	10/14/15	10/15/15	610	2	16945	586	14629	1	1.4	3.8	3	830	1500	1141
10/09/15	to	10/15/15	10/16/15	(570)	2	16375	(594)	14035	1	1.2	0.6	3	830	1500	1135.5
10/12/15	to	10/16/15	10/19/15	(190)	1	16185	(202)	13833	1	1.4	2.2	3	830	1500	1139.5
10/13/15	to	10/19/15	10/20/15	5	1	16190	(7)	13826	1	5.8	3.2	3	830	1500	1135.8
10/14/15	to	10/20/15	10/21/15	(1015)	1	15175	(1027)	12799	1	1.6	6	3	830	1500	1119.9
10/15/15	to	10/21/15	10/22/15	(465)	2	14710	(489)	12310	1	1.8	5	3	830	1500	1134.8
10/16/15	to	10/22/15	10/23/15	345	1	15055	333	12643	1	2.4	3.2	3	830	1500	1140
10/19/15	to	10/23/15	10/26/15	(115)	2	14940	(139)	12504	1	2.4	5.2	3	830	1500	1133.4
10/20/15	to	10/26/15	10/27/15	390	1	15330	378	12882	1	2.4	1.8	3	830	1500	1120.1
10/21/15	to	10/27/15	10/28/15	1490	1	16820	1478	14360	1	0.2	2	3	830	1500	1153.7
10/22/15	to	10/28/15	10/29/15	75	2	16895	51	14411	1	2	4.2	3	830	1500	1139.9
10/23/15	to	10/29/15	10/30/15	(35)	1	16860	(47)	14364	1	1.4	2.6	3	830	1500	1136.7
10/26/15	to	10/30/15	11/02/15	410	2	17270	386	14750	1	1.4	2	3	830	1500	1158.5
10/27/15	to	11/02/15	11/03/15	745	2	18015	721	15471	1	1.4	0.4	3	830	1500	1166.2
10/28/15	to	11/03/15	11/04/15	205	1	18220	193	15664	1	2.2	1	3	830	1500	1165
10/29/15	to	11/04/15	11/05/15	(15)	1	18205	(27)	15637	1	5.8	2.8	3	830	1500	1165.6
10/30/15	to	11/05/15	11/06/15	585	1	18790	573	16210	1	6	3.6	3	830	1500	1177.5
11/02/15	to	11/06/15	11/09/15	(805)	2	17985	(829)	15381	1	5.4	3.2	3	830	1500	1159.5
11/03/15	to	11/09/15	11/10/15	(220)	1	17765	(232)	15149	1	2.8	1	3	830	1500	1165.4
11/04/15	to	11/10/15	11/11/15	(460)	3	17305	(496)	14653	1	0.6	0.2	3	830	1500	1153.6
11/05/15	to	11/11/15	11/12/15	610	1	17915	598	15251	1	3	0.2	3	830	1500	1132
11/06/15	to	11/12/15	11/13/15	95	2	18010	71	15322	1	3.4	0.2	3	830	1500	1122.2
11/09/15	to	11/13/15	11/16/15	510	1	18520	498	15820	1	5.6	0.8	3	830	1500	1131.2
11/10/15	to	11/16/15	11/17/15	(165)	1	18355	(177)	15643	1	5.6	4.4	3	830	1500	1130
11/11/15	to	11/17/15	11/18/15	(870)	1	17485	(882)	14761	1	5	2	3	830	1500	1148.9
11/12/15	to	11/18/15	11/19/15	(200)	1	17285	(212)	14549	1	0.2	3.4	3	830	1500	1142.2
11/13/15	to	11/19/15	11/20/15	135	1	17420	123	14672	1	0.2	5.2	3	830	1500	1151.7
11/16/15	to	11/20/15	11/23/15	220	3	17640	184	14856	1	0.6	5.2	3	830	1500	1158
11/17/15	to	11/23/15	11/24/15	250	2	17890	226	15082	1	1.2	5.2	3	830	1500	1165.3
11/18/15	to	11/24/15	11/25/15	380	1	18270	368	15450	1	0.4	3.4	3	830	1500	1175.3
11/23/15	to	11/27/15	11/30/15	(250)	2	18020	(274)	15176	1	1.2	3.2	3	830	1500	1177.3
11/24/15	to	11/30/15	12/01/15	390	3	18410	354	15530	1	0.6	3.2	3	830	1500	1182.4
11/25/15	to	12/01/15	12/02/15	530	1	18940	518	16048	1	6	5.4	3	830	1500	1172.4
11/26/15	to	12/02/15	12/03/15	1350	1	20290	1338	17386	1	0.6	2	3	830	1500	1149.6
11/27/15	to	12/03/15	12/04/15	(220)	2	20070	(244)	17142	1	0.6	2.4	3	830	1500	1162

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
11/30/15	to	12/04/15	12/07/15	(310)	2	19760	(334)	16808	1	0.6	1.4	3	830	1500	1144.7
12/01/15	to	12/07/15	12/08/15	(500)	2	19260	(524)	16284	1	0.8	1.2	3	830	1500	1135.2
12/02/15	to	12/08/15	12/09/15	(600)	2	18660	(624)	15660	1	1.4	1.2	3	830	1500	1121.1
12/03/15	to	12/09/15	12/10/15	(380)	2	18280	(404)	15256	1	1.4	1.6	3	830	1500	1125.6
12/04/15	to	12/10/15	12/11/15	485	2	18765	461	15717	1	1.4	1.6	3	830	1500	1101.2
12/07/15	to	12/11/15	12/14/15	775	2	19540	751	16468	1	5.8	1.6	3	830	1500	1091
12/08/15	to	12/14/15	12/15/15	370	1	19910	358	16826	1	5.6	4	3	830	1500	1112.2
12/09/15	to	12/15/15	12/16/15	540	1	20450	528	17354	1	0.8	3.4	3	830	1500	1128.5
12/10/15	to	12/16/15	12/17/15	(595)	2	19855	(619)	16735	1	0.4	5.8	3	830	1500	1109.7
12/11/15	to	12/17/15	12/18/15	615	1	20470	603	17338	1	2.8	0.4	3	830	1500	1097.5
12/14/15	to	12/18/15	12/21/15	(710)	2	19760	(734)	16604	1	1.6	0.4	3	830	1500	1107
12/15/15	to	12/21/15	12/22/15	(630)	2	19130	(654)	15950	1	5.8	3.2	3	830	1500	1119.2
12/16/15	to	12/22/15	12/23/15	385	1	19515	373	16323	1	0.2	4.8	3	830	1500	1128.9
12/21/15	to	12/25/15	12/28/15	(10)	1	19505	(22)	16301	1	4.4	4.4	3	830	1500	1127
12/22/15	to	12/28/15	12/29/15	260	1	19765	248	16549	1	3.6	4.8	3	830	1500	1142.8
12/23/15	to	12/29/15	12/30/15	545	1	20310	533	17082	1	6	6	3	830	1500	1126.5
12/24/15	to	12/30/15	12/31/15	(750)	2	19560	(774)	16308	1	3.6	2.8	3	830	1500	1114
12/28/15	to	01/01/16	01/04/16	(445)	2	19115	(469)	15839	1	2.2	2	3	830	1500	1089.7
12/29/15	to	01/04/16	01/05/16	0	1	19115	(12)	15827	1	2.4	5.4	3	830	1500	1091.7
12/30/15	to	01/05/16	01/06/16	140	1	19255	128	15955	1	6	0.2	3	830	1500	1074.7
12/31/15	to	01/06/16	01/07/16	190	2	19445	166	16121	1	6	0.6	3	830	1500	1041.1
01/01/16	to	01/07/16	01/08/16	350	2	19795	326	16447	1	5.8	0.6	3	830	1500	1025.3
01/04/16	to	01/08/16	01/11/16	575	1	20370	563	17010	1	3.6	0.4	3	830	1500	1021.8
01/05/16	to	01/11/16	01/12/16	(490)	3	19880	(526)	16484	1	3.6	0.4	3	830	1500	1020.2
01/06/16	to	01/12/16	01/13/16	1890	1	21770	1878	18362	1	3.6	0.4	3	830	1500	990.2
01/07/16	to	01/13/16	01/14/16	(365)	2	21405	(389)	17973	1	3.4	0.2	3	830	1500	1004.4
01/08/16	to	01/14/16	01/15/16	210	3	21615	174	18147	1	3.4	0.2	3	830	1500	989.8
01/12/16	to	01/18/16	01/19/16	(400)	2	21215	(424)	17723	1	3.4	0.8	3	830	1500	973.7
01/13/16	to	01/19/16	01/20/16	430	2	21645	406	18129	1	3	0.8	3	830	1500	981.8
01/14/16	to	01/20/16	01/21/16	980	2	22625	956	19085	1	3.8	0.8	3	830	1500	975.7
01/15/16	to	01/21/16	01/22/16	275	2	22900	251	19336	1	3.2	2.2	3	830	1500	998.1
01/18/16	to	01/22/16	01/25/16	105	2	23005	81	19417	1	2.6	2.2	3	830	1500	978.3
01/19/16	to	01/25/16	01/26/16	620	3	23625	584	20001	1	3.4	2.4	3	830	1500	997
01/20/16	to	01/26/16	01/27/16	(420)	2	23205	(444)	19557	1	2.6	3.8	3	830	1500	982.2
01/21/16	to	01/27/16	01/28/16	(650)	2	22555	(674)	18883	1	2.4	3.6	3	830	1500	980.4
01/22/16	to	01/28/16	01/29/16	15	2	22570	(9)	18874	1	4.8	1	3	830	1500	1016.8
01/25/16	to	01/29/16	02/01/16	(340)	2	22230	(364)	18510	1	5.8	1	3	830	1500	1009.8
01/26/16	to	02/01/16	02/02/16	465	1	22695	453	18963	1	5.8	1.2	3	830	1500	992
01/27/16	to	02/02/16	02/03/16	1550	2	24245	1526	20489	1	4	1.2	3	830	1500	991
01/28/16	to	02/03/16	02/04/16	(325)	2	23920	(349)	20140	1	0.2	1	3	830	1500	993.2
01/29/16	to	02/04/16	02/05/16	1000	1	24920	988	21128	1	6	0.8	3	830	1500	970.1
02/01/16	to	02/05/16	02/08/16	45	1	24965	33	21161	1	5.6	5	3	830	1500	953.1
02/02/16	to	02/08/16	02/09/16	(840)	2	24125	(864)	20297	1	1.6	5.2	3	830	1500	944.2
02/03/16	to	02/09/16	02/10/16	1060	2	25185	1036	21333	1	0.6	5	3	830	1500	943.2
02/04/16	to	02/10/16	02/11/16	330	2	25515	306	21639	1	0.2	5.2	3	830	1500	934.9
02/05/16	to	02/11/16	02/12/16	435	1	25950	423	22062	1	0.2	5.4	3	830	1500	951.3
02/09/16	to	02/15/16	02/16/16	525	2	26475	501	22563	1	4	0.6	3	830	1500	974.1
02/10/16	to	02/16/16	02/17/16	(585)	2	25890	(609)	21954	1	4.2	6	3	830	1500	992.5
02/11/16	to	02/17/16	02/18/16	(125)	2	25765	(149)	21805	1	1.8	1.8	3	830	1500	987.9
02/12/16	to	02/18/16	02/19/16	(170)	3	25595	(206)	21599	1	3	1.8	3	830	1500	992.1
02/15/16	to	02/19/16	02/22/16	360	2	25955	336	21935	1	1.8	2	3	830	1500	999.8
02/16/16	to	02/22/16	02/23/16	70	2	26025	46	21981	1	3.2	2	3	830	1500	993.3
02/17/16	to	02/23/16	02/24/16	1145	1	27170	1133	23114	1	2	2	3	830	1500	1005.4
02/18/16	to	02/24/16	02/25/16	160	1	27330	148	23262	1	5.6	5.8	3	830	1500	1013.6
02/19/16	to	02/25/16	02/26/16	(90)	1	27240	(102)	23160	1	4	1.2	3	830	1500	1019.1
02/22/16	to	02/26/16	02/29/16	230	1	27470	218	23378	1	5.6	6	3	830	1500	1017
02/23/16	to	02/29/16	03/01/16	(700)	1	26770	(712)	22666	1	5.6	4.6	3	830	1500	1038
02/24/16	to	03/01/16	03/02/16	70	2	26840	46	22712	1	0.4	1.4	3	830	1500	1047.9

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
02/25/16	to	03/02/16	03/03/16	(100)	2	26740	(124)	22588	1	0.2	0.6	3	830	1500	1057.7
02/26/16	to	03/03/16	03/04/16	880	2	27620	856	23444	1	0.2	0.4	3	830	1500	1063.9
02/29/16	to	03/04/16	03/07/16	(255)	2	27365	(279)	23165	1	2	3.4	3	830	1500	1077.8
03/01/16	to	03/07/16	03/08/16	960	1	28325	948	24113	1	0.2	2.8	3	830	1500	1051.9
03/02/16	to	03/08/16	03/09/16	300	2	28625	276	24389	1	1.2	4.4	3	830	1500	1057.3
03/03/16	to	03/09/16	03/10/16	(435)	1	28190	(447)	23942	1	5.2	6	3	830	1500	1046.4
03/04/16	to	03/10/16	03/11/16	640	1	28830	628	24570	1	5.4	5.8	3	830	1500	1069.1
03/07/16	to	03/11/16	03/14/16	(120)	2	28710	(144)	24426	1	6	5.2	3	830	1500	1065.4
03/08/16	to	03/14/16	03/15/16	350	1	29060	338	24764	1	6	5.2	3	830	1500	1048.8
03/09/16	to	03/15/16	03/16/16	(30)	2	29030	(54)	24710	1	5.4	1.2	3	830	1500	1055.7
03/10/16	to	03/16/16	03/17/16	865	1	29895	853	25563	1	6	4.4	3	830	1500	1073.5
03/11/16	to	03/17/16	03/18/16	300	1	30195	288	25851	1	5	4.6	3	830	1500	1084.5
03/14/16	to	03/18/16	03/21/16	110	1	30305	98	25949	1	1.8	1.6	3	830	1500	1082.6
03/15/16	to	03/21/16	03/22/16	(525)	2	29780	(549)	25400	1	2.6	1.6	3	830	1500	1080.8
03/16/16	to	03/22/16	03/23/16	105	2	29885	81	25481	1	1.2	1.8	3	830	1500	1060.9
03/17/16	to	03/23/16	03/24/16	(525)	2	29360	(549)	24932	1	1.2	1.8	3	830	1500	1063.1
03/21/16	to	03/25/16	03/28/16	(110)	1	29250	(122)	24810	1	0.6	4.6	3	830	1500	1063.6
03/22/16	to	03/28/16	03/29/16	1635	1	30885	1623	26433	1	1	2.8	3	830	1500	1095.6
03/23/16	to	03/29/16	03/30/16	155	2	31040	131	26564	1	2.4	0.2	3	830	1500	1095.8
03/24/16	to	03/30/16	03/31/16	(385)	2	30655	(409)	26155	1	0.2	0.2	3	830	1500	1098.1
03/25/16	to	03/31/16	04/01/16	320	3	30975	284	26439	1	0.2	0.2	3	830	1500	1102.4
03/28/16	to	04/01/16	04/04/16	520	2	31495	496	26935	1	0.2	0.2	3	830	1500	1093.6
03/29/16	to	04/04/16	04/05/16	(290)	2	31205	(314)	26621	1	0.2	0.2	3	830	1500	1080.6
03/30/16	to	04/05/16	04/06/16	(120)	2	31085	(144)	26477	1	5.2	4.4	3	830	1500	1092.2
03/31/16	to	04/06/16	04/07/16	(735)	2	30350	(759)	25718	1	5.2	5.4	3	830	1500	1079
04/01/16	to	04/07/16	04/08/16	(1235)	4	29115	(1283)	24435	1	0.4	0.2	3	830	1500	1082.7
04/04/16	to	04/08/16	04/11/16	145	2	29260	121	24556	1	1.8	0.2	3	830	1500	1077
04/05/16	to	04/11/16	04/12/16	(480)	2	28780	(504)	24052	1	1.8	0.2	3	830	1500	1091.3
04/06/16	to	04/12/16	04/13/16	855	1	29635	843	24895	1	5.2	2.8	3	830	1500	1116.3
04/07/16	to	04/13/16	04/14/16	65	1	29700	53	24948	1	1.8	0.2	3	830	1500	1113.1
04/08/16	to	04/14/16	04/15/16	(120)	2	29580	(144)	24804	1	6	6	3	830	1500	1116.6
04/11/16	to	04/15/16	04/18/16	665	1	30245	653	25457	1	6	4.6	3	830	1500	1124.9
04/12/16	to	04/18/16	04/19/16	(125)	2	30120	(149)	25308	1	2.6	4.6	3	830	1500	1126
04/13/16	to	04/19/16	04/20/16	(155)	1	29965	(167)	25141	1	6	0.6	3	830	1500	1127.9
04/14/16	to	04/20/16	04/21/16	400	1	30365	388	25529	1	3	5.6	3	830	1500	1121
04/15/16	to	04/21/16	04/22/16	(80)	2	30285	(104)	25425	1	2.2	0.6	3	830	1500	1133.7
04/18/16	to	04/22/16	04/25/16	(495)	2	29790	(519)	24906	1	2.2	0.6	3	830	1500	1124.1
04/19/16	to	04/25/16	04/26/16	85	2	29875	61	24967	1	0.2	0.8	3	830	1500	1138.2
04/20/16	to	04/26/16	04/27/16	(10)	2	29865	(34)	24933	1	0.2	0.2	3	830	1500	1141.6
04/21/16	to	04/27/16	04/28/16	815	2	30680	791	25724	1	0.2	0.2	3	830	1500	1128.6
04/22/16	to	04/28/16	04/29/16	485	2	31165	461	26185	1	0.2	0.2	3	830	1500	1118.7
04/25/16	to	04/29/16	05/02/16	100	2	31265	76	26261	1	0.2	0.2	3	830	1500	1126
04/26/16	to	05/02/16	05/03/16	130	2	31395	106	26367	1	0.2	2.6	3	830	1500	1106.5
04/27/16	to	05/03/16	05/04/16	(610)	3	30785	(646)	25721	1	0.2	2.6	3	830	1500	1098.9
04/28/16	to	05/04/16	05/05/16	110	2	30895	86	25807	1	5.6	1	3	830	1500	1093.1
04/29/16	to	05/05/16	05/06/16	475	1	31370	463	26270	1	4	1	3	830	1500	1102.5
05/02/16	to	05/06/16	05/09/16	145	1	31515	133	26403	1	4.8	1	3	830	1500	1103.6
05/03/16	to	05/09/16	05/10/16	(365)	1	31150	(377)	26026	1	4.8	0.2	3	830	1500	1114.4
05/04/16	to	05/10/16	05/11/16	585	1	31735	573	26599	1	4.6	0.2	3	830	1500	1098.9
05/05/16	to	05/11/16	05/12/16	475	1	32210	463	27062	1	4.8	2.6	3	830	1500	1093.3
05/06/16	to	05/12/16	05/13/16	(260)	1	31950	(272)	26790	1	1.4	4.8	3	830	1500	1089
05/09/16	to	05/13/16	05/16/16	385	1	32335	373	27163	1	0.8	5.2	3	830	1500	1102.2
05/10/16	to	05/16/16	05/17/16	250	2	32585	226	27389	1	5.2	5.2	3	830	1500	1084.4
05/11/16	to	05/17/16	05/18/16	(1755)	3	30830	(1791)	25598	1	5.4	0.6	3	830	1500	1089.4
05/12/16	to	05/18/16	05/19/16	445	3	31275	409	26007	1	0.2	1.4	3	830	1500	1081.9
05/13/16	to	05/19/16	05/20/16	115	2	31390	91	26098	1	1.4	1.4	3	830	1500	1100.7
05/16/16	to	05/20/16	05/23/16	(270)	2	31120	(294)	25804	1	1.4	1.4	3	830	1500	1096.8
05/17/16	to	05/23/16	05/24/16	740	2	31860	716	26520	1	4	1.4	3	830	1500	1122.8

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
05/18/16	to	05/24/16	05/25/16	(110)	1	31750	(122)	26398	1	5.8	1.6	3	830	1500	1128.5
05/19/16	to	05/25/16	05/26/16	(155)	1	31595	(167)	26231	1	6	5	3	830	1500	1128
05/20/16	to	05/26/16	05/27/16	180	2	31775	156	26387	1	6	5.2	3	830	1500	1138.6
05/24/16	to	05/30/16	05/31/16	(55)	1	31720	(67)	26320	1	6	5	3	830	1500	1142
05/25/16	to	05/31/16	06/01/16	(620)	1	31100	(632)	25688	1	6	3.6	3	830	1500	1149.9
05/26/16	to	06/01/16	06/02/16	560	1	31660	548	26236	1	0.6	5	3	830	1500	1159.2
05/27/16	to	06/02/16	06/03/16	(220)	2	31440	(244)	25992	1	0.4	5	3	830	1500	1150.4
05/30/16	to	06/03/16	06/06/16	5	2	31445	(19)	25973	1	0.6	4.8	3	830	1500	1164.9
05/31/16	to	06/06/16	06/07/16	95	1	31540	83	26056	1	3.4	5.6	3	830	1500	1168.1
06/01/16	to	06/07/16	06/08/16	45	1	31585	33	26089	1	6	5.2	3	830	1500	1177.1
06/02/16	to	06/08/16	06/09/16	10	1	31595	(2)	26087	1	4.8	5.6	3	830	1500	1168.3
06/03/16	to	06/09/16	06/10/16	130	1	31725	118	26205	1	5.8	5.4	3	830	1500	1152.8
06/06/16	to	06/10/16	06/13/16	150	1	31875	138	26343	1	5	5.2	3	830	1500	1137.5
06/07/16	to	06/13/16	06/14/16	120	1	31995	108	26451	1	6	6	3	830	1500	1137.7
06/08/16	to	06/14/16	06/15/16	20	1	32015	8	26459	1	6	5.2	3	830	1500	1137.6
06/09/16	to	06/15/16	06/16/16	(190)	2	31825	(214)	26245	1	0.4	0.2	3	830	1500	1138.8
06/10/16	to	06/16/16	06/17/16	(195)	2	31630	(219)	26026	1	1	0.2	3	830	1500	1131.8
06/13/16	to	06/17/16	06/20/16	440	3	32070	404	26430	1	0.6	0.8	3	830	1500	1144.2
06/14/16	to	06/20/16	06/21/16	(180)	2	31890	(204)	26226	1	0.6	1.2	3	830	1500	1142.3
06/15/16	to	06/21/16	06/22/16	(100)	2	31790	(124)	26102	1	0.4	1	3	830	1500	1137.1
06/16/16	to	06/22/16	06/23/16	355	2	32145	331	26433	1	0.4	1	3	830	1500	1164.2
06/17/16	to	06/23/16	06/24/16	1460	2	33605	1436	27869	1	2.4	2.2	3	830	1500	1111.1
06/20/16	to	06/24/16	06/27/16	1185	2	34790	1161	29030	1	3.6	0.8	3	830	1500	1072.8
06/21/16	to	06/27/16	06/28/16	575	2	35365	551	29581	1	1.2	0.8	3	830	1500	1098.9
06/22/16	to	06/28/16	06/29/16	370	3	35735	334	29915	1	3.8	0.8	3	830	1500	1122.6
06/23/16	to	06/29/16	06/30/16	180	2	35915	156	30071	1	0.6	2.2	3	830	1500	1141.8
06/24/16	to	06/30/16	07/01/16	90	3	36005	54	30125	1	0.4	0.2	3	830	1500	1147.3
06/28/16	to	07/04/16	07/05/16	595	1	36600	583	30708	1	5.6	2.2	3	830	1500	1129.5
06/29/16	to	07/05/16	07/06/16	(550)	2	36050	(574)	30134	1	2.8	0.2	3	830	1500	1137.2
06/30/16	to	07/06/16	07/07/16	(285)	2	35765	(309)	29825	1	0.6	0.2	3	830	1500	1139.6
07/01/16	to	07/07/16	07/08/16	(810)	2	34955	(834)	28991	1	4.4	5	3	830	1500	1166.5
07/04/16	to	07/08/16	07/11/16	255	2	35210	231	29222	1	3	5.2	3	830	1500	1181.1
07/05/16	to	07/11/16	07/12/16	(505)	2	34705	(529)	28693	1	3.6	5.2	3	830	1500	1195.1
07/06/16	to	07/12/16	07/13/16	(435)	2	34270	(459)	28234	1	0.6	5.8	3	830	1500	1193
07/07/16	to	07/13/16	07/14/16	90	2	34360	66	28300	1	0.8	5.2	3	830	1500	1193.7
07/08/16	to	07/14/16	07/15/16	80	2	34440	56	28356	1	0.4	0.2	3	830	1500	1195.9
07/11/16	to	07/15/16	07/18/16	310	2	34750	286	28642	1	1.4	4.2	3	830	1500	1197.9
07/12/16	to	07/18/16	07/19/16	295	1	35045	283	28925	1	1.4	4.2	3	830	1500	1192.7
07/13/16	to	07/19/16	07/20/16	445	1	35490	433	29358	1	1.4	5	3	830	1500	1201.2
07/14/16	to	07/20/16	07/21/16	375	1	35865	363	29721	1	1.4	0.6	3	830	1500	1193.2
07/15/16	to	07/21/16	07/22/16	(500)	2	35365	(524)	29197	1	2.6	5.2	3	830	1500	1203.3
07/18/16	to	07/22/16	07/25/16	(355)	2	35010	(379)	28818	1	2.6	5.4	3	830	1500	1201.1
07/19/16	to	07/25/16	07/26/16	180	1	35190	168	28986	1	0.2	5.2	3	830	1500	1207
07/20/16	to	07/26/16	07/27/16	(55)	1	35135	(67)	28919	1	5.2	5.6	3	830	1500	1209.2
07/21/16	to	07/27/16	07/28/16	(30)	1	35105	(42)	28877	1	5.4	6	3	830	1500	1206.9
07/22/16	to	07/28/16	07/29/16	(680)	2	34425	(704)	28173	1	2	0.2	3	830	1500	1213.5
07/25/16	to	07/29/16	08/01/16	55	1	34480	43	28216	1	3.6	5.6	3	830	1500	1211.2
07/26/16	to	08/01/16	08/02/16	(835)	1	33645	(847)	27369	1	3.6	5.6	3	830	1500	1193.6
07/27/16	to	08/02/16	08/03/16	210	1	33855	198	27567	1	5.6	5.6	3	830	1500	1204.6
07/28/16	to	08/03/16	08/04/16	(70)	1	33785	(82)	27485	1	3.6	4.6	3	830	1500	1203.9
07/29/16	to	08/04/16	08/05/16	(5)	1	33780	(17)	27468	1	5.4	4.8	3	830	1500	1221.6
08/01/16	to	08/05/16	08/08/16	(75)	2	33705	(99)	27369	1	5.2	4.8	3	830	1500	1220.9
08/02/16	to	08/08/16	08/09/16	0	1	33705	(12)	27357	1	6	4.6	3	830	1500	1223.1
08/03/16	to	08/09/16	08/10/16	80	1	33785	68	27425	1	6	4.6	3	830	1500	1214.8
08/04/16	to	08/10/16	08/11/16	(185)	2	33600	(209)	27216	1	5	3.6	3	830	1500	1221.3
08/05/16	to	08/11/16	08/12/16	20	1	33620	8	27224	1	6	4.6	3	830	1500	1220.6
08/08/16	to	08/12/16	08/15/16	(335)	2	33285	(359)	26865	1	6	4	3	830	1500	1233.6
08/09/16	to	08/15/16	08/16/16	265	1	33550	253	27118	1	6	3.6	3	830	1500	1224.1

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
08/10/16	to	08/16/16	08/17/16	(35)	2	33515	(59)	27059	1	2.4	0.6	3	830	1500	1220.4
08/11/16	to	08/17/16	08/18/16	335	1	33850	323	27382	1	2.4	3.2	3	830	1500	1229.2
08/12/16	to	08/18/16	08/19/16	(270)	2	33580	(294)	27088	1	0.4	0.6	3	830	1500	1228.3
08/15/16	to	08/19/16	08/22/16	370	1	33950	358	27446	1	0.2	3.4	3	830	1500	1231.7
08/16/16	to	08/22/16	08/23/16	115	1	34065	103	27549	1	4.8	4.6	3	830	1500	1240.6
08/17/16	to	08/23/16	08/24/16	490	2	34555	466	28015	1	3.4	3.2	3	830	1500	1229.7
08/18/16	to	08/24/16	08/25/16	(295)	1	34260	(307)	27708	1	6	3	3	830	1500	1233.1
08/19/16	to	08/25/16	08/26/16	(270)	1	33990	(282)	27426	1	3.2	4	3	830	1500	1231.8
08/22/16	to	08/26/16	08/29/16	(190)	1	33800	(202)	27224	1	3.8	2	3	830	1500	1238.5
08/23/16	to	08/29/16	08/30/16	(80)	1	33720	(92)	27132	1	2.8	4.2	3	830	1500	1239.6
08/24/16	to	08/30/16	08/31/16	235	1	33955	223	27355	1	2.8	2.4	3	830	1500	1234.2
08/25/16	to	08/31/16	09/01/16	(65)	1	33890	(77)	27278	1	1.8	2.8	3	830	1500	1231.8
08/26/16	to	09/01/16	09/02/16	310	1	34200	298	27576	1	0.6	3.4	3	830	1500	1245.3
08/30/16	to	09/05/16	09/06/16	(260)	1	33940	(272)	27304	1	4.2	3.2	3	830	1500	1247
08/31/16	to	09/06/16	09/07/16	(80)	2	33860	(104)	27200	1	3.2	1.8	3	830	1500	1254.2
09/01/16	to	09/07/16	09/08/16	(20)	1	33840	(32)	27168	1	4.6	4	3	830	1500	1249.2
09/02/16	to	09/08/16	09/09/16	720	1	34560	708	27876	1	4.6	5.4	3	830	1500	1208.1
09/05/16	to	09/09/16	09/12/16	(665)	2	33895	(689)	27187	1	4.4	4.8	3	830	1500	1229.8
09/06/16	to	09/12/16	09/13/16	(925)	2	32970	(949)	26238	1	0.2	2.4	3	830	1500	1206.9
09/07/16	to	09/13/16	09/14/16	200	1	33170	188	26426	1	4.4	4.8	3	830	1500	1202.4
09/08/16	to	09/14/16	09/15/16	475	1	33645	463	26889	1	4.4	5.6	3	830	1500	1219.5
09/09/16	to	09/15/16	09/16/16	15	2	33660	(9)	26880	1	1.4	5.8	3	830	1500	1218.8
09/12/16	to	09/16/16	09/19/16	35	2	33695	11	26891	1	1	6	3	830	1500	1227.4
09/13/16	to	09/19/16	09/20/16	340	1	34035	328	27219	1	6	5.4	3	830	1500	1221.1
09/14/16	to	09/20/16	09/21/16	190	2	34225	166	27385	1	1	5.4	3	830	1500	1240.6
09/15/16	to	09/21/16	09/22/16	230	2	34455	206	27591	1	1	5.4	3	830	1500	1257.7
09/16/16	to	09/22/16	09/23/16	410	1	34865	398	27989	1	1	5.4	3	830	1500	1248.6
09/19/16	to	09/23/16	09/26/16	30	2	34895	6	27995	1	1	5.6	3	830	1500	1235
09/20/16	to	09/26/16	09/27/16	390	1	35285	378	28373	1	1.4	2.8	3	830	1500	1241.7
09/21/16	to	09/27/16	09/28/16	25	2	35310	1	28374	1	1.4	0.8	3	830	1500	1250.8
09/22/16	to	09/28/16	09/29/16	600	2	35910	576	28950	1	1.8	1.2	3	830	1500	1234.3
09/23/16	to	09/29/16	09/30/16	620	2	36530	596	29546	1	0.2	1	3	830	1500	1243.7
09/26/16	to	09/30/16	10/03/16	375	3	36905	339	29885	1	0.2	1	3	830	1500	1242
09/27/16	to	10/03/16	10/04/16	(45)	2	36860	(69)	29816	1	0.2	0.8	3	830	1500	1235.8
09/28/16	to	10/04/16	10/05/16	(555)	2	36305	(579)	29237	1	2	2.2	3	830	1500	1242.7
09/29/16	to	10/05/16	10/06/16	(310)	3	35995	(346)	28891	1	0.2	1.4	3	830	1500	1242.7
09/30/16	to	10/06/16	10/07/16	(90)	2	35905	(114)	28777	1	6	0.2	3	830	1500	1229.5
10/03/16	to	10/07/16	10/10/16	100	3	36005	64	28841	1	5.6	1.6	3	830	1500	1248.4
10/04/16	to	10/10/16	10/11/16	840	1	36845	828	29669	1	5.6	1	3	830	1500	1224.3
10/05/16	to	10/11/16	10/12/16	(10)	1	36835	(22)	29647	1	0.4	2.8	3	830	1500	1220.9
10/06/16	to	10/12/16	10/13/16	(345)	3	36490	(381)	29266	1	0.2	0.6	3	830	1500	1212.3
10/07/16	to	10/13/16	10/14/16	95	1	36585	83	29349	1	2.2	2.6	3	830	1500	1208.7
10/10/16	to	10/14/16	10/17/16	(305)	2	36280	(329)	29020	1	2.4	2.6	3	830	1500	1207.8
10/11/16	to	10/17/16	10/18/16	(120)	3	36160	(156)	28864	1	5	2.6	3	830	1500	1210.8
10/12/16	to	10/18/16	10/19/16	(555)	2	35605	(579)	28285	1	5	2.6	3	830	1500	1216.8
10/13/16	to	10/19/16	10/20/16	(515)	2	35090	(539)	27746	1	1.4	3	3	830	1500	1216.5
10/14/16	to	10/20/16	10/21/16	0	0	35090	0	27746	0	0					1214.1
10/17/16	to	10/21/16	10/24/16	0	0	35090	0	27746	0	0					1221.6
10/18/16	to	10/24/16	10/25/16	0	0	35090	0	27746	0	0					1212.7
10/19/16	to	10/25/16	10/26/16	0	0	35090	0	27746	0	0					1200
10/20/16	to	10/26/16	10/27/16	0	0	35090	0	27746	1	2.4	6	3	830	1500	1182
10/21/16	to	10/27/16	10/28/16	30	1	35120	18	27764	1	2.4	5	3	830	1500	1184.1
10/24/16	to	10/28/16	10/31/16	(160)	1	34960	(172)	27592	1	2.4	4.2	3	830	1500	1189.6
10/25/16	to	10/31/16	11/01/16	495	1	35455	483	28075	1	2.4	5	3	830	1500	1171.8
10/26/16	to	11/01/16	11/02/16	75	2	35530	51	28126	1	1.4	4.2	3	830	1500	1156.9
10/27/16	to	11/02/16	11/03/16	(460)	1	35070	(472)	27654	1	1.4	4	3	830	1500	1152.2
10/28/16	to	11/03/16	11/04/16	205	1	35275	193	27847	1	1.4	4	3	830	1500	1159.5
10/31/16	to	11/04/16	11/07/16	(245)	3	35030	(281)	27566	1	0.2	0.2	3	830	1500	1189.4

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
11/01/16	to	11/07/16	11/08/16	(230)	3	34800	(266)	27300	1	0.2	0.2	3	830	1500	1189.9
11/02/16	to	11/08/16	11/09/16	520	4	35320	472	27772	1	0.2	0.2	3	830	1500	1228.7
11/03/16	to	11/09/16	11/10/16	270	2	35590	246	28018	1	0.2	0.6	3	830	1500	1252.8
11/04/16	to	11/10/16	11/11/16	(965)	2	34625	(989)	27029	1	0.2	1.8	3	830	1500	1281
11/07/16	to	11/11/16	11/14/16	(5)	2	34620	(29)	27000	1	0.6	1.6	3	830	1500	1296.9
11/08/16	to	11/14/16	11/15/16	(225)	1	34395	(237)	26763	1	0.6	1.6	3	830	1500	1299.1
11/09/16	to	11/15/16	11/16/16	175	3	34570	139	26902	1	2.6	1	3	830	1500	1299.8
11/10/16	to	11/16/16	11/17/16	420	2	34990	396	27298	1	3	4	3	830	1500	1308.1
11/11/16	to	11/17/16	11/18/16	(140)	1	34850	(152)	27146	1	3	0.4	3	830	1500	1313.6
11/14/16	to	11/18/16	11/21/16	(85)	1	34765	(97)	27049	1	1	4.4	3	830	1500	1319.8
11/15/16	to	11/21/16	11/22/16	455	1	35220	443	27492	1	1	3	3	830	1500	1332.5
11/16/16	to	11/22/16	11/23/16	0	0	35220	0	27492	1	3	5.2	3	830	1500	1340.1
11/21/16	to	11/25/16	11/28/16	790	1	36010	778	28270	1	0.4	1.8	3	830	1500	1328.9
11/22/16	to	11/28/16	11/29/16	330	1	36340	318	28588	1	3	3.6	3	830	1500	1326.7
11/23/16	to	11/29/16	11/30/16	(665)	1	35675	(677)	27911	1	0.6	2.8	3	830	1500	1321.9
11/24/16	to	11/30/16	12/01/16	525	1	36200	513	28424	1	0.6	0.2	3	830	1500	1314.5
11/25/16	to	12/01/16	12/02/16	(255)	2	35945	(279)	28145	1	0.6	0.2	3	830	1500	1311.2
11/28/16	to	12/02/16	12/05/16	560	1	36505	548	28693	1	1.4	4.6	3	830	1500	1337.6
11/29/16	to	12/05/16	12/06/16	65	2	36570	41	28734	1	4.2	1.2	3	830	1500	1346.6
11/30/16	to	12/06/16	12/07/16	640	1	37210	628	29362	1	4.2	1.6	3	830	1500	1360
12/01/16	to	12/07/16	12/08/16	940	1	38150	928	30290	1	0.4	0.8	3	830	1500	1387.1
12/02/16	to	12/08/16	12/09/16	(155)	2	37995	(179)	30111	1	0.4	0.8	3	830	1500	1386.1
12/05/16	to	12/09/16	12/12/16	880	2	38875	856	30967	1	0.2	0.2	3	830	1500	1372.5
12/06/16	to	12/12/16	12/13/16	(1185)	4	37690	(1233)	29734	1	0.6	0.8	3	830	1500	1374.8
12/07/16	to	12/13/16	12/14/16	75	3	37765	39	29773	1	0.2	0.2	3	830	1500	1358
12/08/16	to	12/14/16	12/15/16	(470)	1	37295	(482)	29291	1	5.4	1.4	3	830	1500	1369.1
12/09/16	to	12/15/16	12/16/16	(630)	1	36665	(642)	28649	1	3	5.4	3	830	1500	1366
12/12/16	to	12/16/16	12/19/16	(80)	1	36585	(92)	28557	1	2.6	5	3	830	1500	1373.4
12/13/16	to	12/19/16	12/20/16	260	1	36845	248	28805	1	2.6	6	3	830	1500	1382.7
12/14/16	to	12/20/16	12/21/16	475	1	37320	463	29268	1	4.4	0.8	3	830	1500	1374.8
12/15/16	to	12/21/16	12/22/16	575	2	37895	551	29819	1	2.6	2.4	3	830	1500	1363.4
12/16/16	to	12/22/16	12/23/16	340	2	38235	316	30135	1	4.4	2	3	830	1500	1369.9
12/20/16	to	12/26/16	12/27/16	305	2	38540	281	30416	1	2	1.6	3	830	1500	1374.2
12/21/16	to	12/27/16	12/28/16	(115)	2	38425	(139)	30277	1	2.2	6	3	830	1500	1360.5
12/22/16	to	12/28/16	12/29/16	335	1	38760	323	30600	1	5.2	2.6	3	830	1500	1362.4
12/23/16	to	12/29/16	12/30/16	120	1	38880	108	30708	1	3.2	3	3	830	1500	1356.9
12/27/16	to	01/02/17	01/03/17	(660)	1	38220	(672)	30036	1	2	3.2	3	830	1500	1366.3
12/28/16	to	01/03/17	01/04/17	695	2	38915	671	30707	1	1.8	0.4	3	830	1500	1386.1
12/29/16	to	01/04/17	01/05/17	565	2	39480	541	31248	1	1.8	0.4	3	830	1500	1369.9
12/30/16	to	01/05/17	01/06/17	(390)	2	39090	(414)	30834	1	4.6	0.6	3	830	1500	1364.7
01/02/17	to	01/06/17	01/09/17	410	2	39500	386	31220	1	5.6	1	3	830	1500	1355.2
01/03/17	to	01/09/17	01/10/17	(110)	2	39390	(134)	31086	1	5	1.2	3	830	1500	1368.8
01/04/17	to	01/10/17	01/11/17	(135)	2	39255	(159)	30927	1	5	1.2	3	830	1500	1374
01/05/17	to	01/11/17	01/12/17	(455)	3	38800	(491)	30436	1	0.2	0.6	3	830	1500	1358.8
01/06/17	to	01/12/17	01/13/17	(300)	2	38500	(324)	30112	1	5	3.4	3	830	1500	1374
01/10/17	to	01/16/17	01/17/17	350	1	38850	338	30450	1	4.8	3.4	3	830	1500	1352.8
01/11/17	to	01/17/17	01/18/17	130	2	38980	106	30556	1	4.8	0.4	3	830	1500	1357.2
01/12/17	to	01/18/17	01/19/17	(40)	2	38940	(64)	30492	1	4.8	0.2	3	830	1500	1346.3
01/13/17	to	01/19/17	01/20/17	(475)	3	38465	(511)	29981	1	2.2	0.2	3	830	1500	1352.5
01/16/17	to	01/20/17	01/23/17	(580)	3	37885	(616)	29365	1	0.2	0.2	3	830	1500	1347.3
01/17/17	to	01/23/17	01/24/17	1260	3	39145	1224	30589	1	2.8	0.4	3	830	1500	1367
01/18/17	to	01/24/17	01/25/17	70	1	39215	58	30647	1	2.4	0.4	3	830	1500	1382.6
01/19/17	to	01/25/17	01/26/17	355	2	39570	331	30978	1	3.4	0.4	3	830	1500	1376.1
01/20/17	to	01/26/17	01/27/17	(665)	2	38905	(689)	30289	1	3.4	0.2	3	830	1500	1367.5
01/23/17	to	01/27/17	01/30/17	95	1	39000	83	30372	1	6	0.2	3	830	1500	1349.6
01/24/17	to	01/30/17	01/31/17	200	2	39200	176	30548	1	5.2	5.2	3	830	1500	1361
01/25/17	to	01/31/17	02/01/17	(1030)	2	38170	(1054)	29494	1	5.2	4.2	3	830	1500	1359.9
01/26/17	to	02/01/17	02/02/17	(25)	1	38145	(37)	29457	1	5.2	4.4	3	830	1500	1354.2

In-Sample Dates			OOS Date	Osnp	OnT	Equity	NetOsnp	NetEq	ncy	pup	pdn	nx	xop	xt	TF cls
01/27/17	to	02/02/17	02/03/17	(140)	2	38005	(164)	29293	1	5.2	4.4	3	830	1500	1377.7
01/30/17	to	02/03/17	02/06/17	120	2	38125	96	29389	1	4	4.4	3	830	1500	1363.9
01/31/17	to	02/06/17	02/07/17	245	1	38370	233	29622	1	5.2	4.6	3	830	1500	1359.4
02/01/17	to	02/07/17	02/08/17	160	1	38530	148	29770	1	4	4.4	3	830	1500	1355.6
02/02/17	to	02/08/17	02/09/17	720	1	39250	708	30478	1	3.6	2.8	3	830	1500	1376.6
02/03/17	to	02/09/17	02/10/17	(145)	2	39105	(169)	30309	1	3.6	2.6	3	830	1500	1387.9
02/06/17	to	02/10/17	02/13/17	(205)	1	38900	(217)	30092	1	3.6	4.6	3	830	1500	1391.7
02/07/17	to	02/13/17	02/14/17	(145)	2	38755	(169)	29923	1	3.8	3.8	3	830	1500	1398.3
02/08/17	to	02/14/17	02/15/17	470	2	39225	446	30369	1	4	5.4	3	830	1500	1404.6
02/09/17	to	02/15/17	02/16/17	740	2	39965	716	31085	1	0.4	5.4	3	830	1500	1399.2
02/10/17	to	02/16/17	02/17/17	230	2	40195	206	31291	1	1.8	0.6	3	830	1500	1396.4
02/14/17	to	02/20/17	02/21/17	205	1	40400	193	31484	1	4.2	5.8	3	830	1500	1407
02/15/17	to	02/21/17	02/22/17	(35)	2	40365	(59)	31425	1	0.2	0.4	3	830	1500	1402.8
02/16/17	to	02/22/17	02/23/17	725	2	41090	701	32126	1	1	4.6	3	830	1500	1393.6
02/17/17	to	02/23/17	02/24/17	640	1	41730	628	32754	1	1.4	1.6	3	830	1500	1393.5
02/20/17	to	02/24/17	02/27/17	845	1	42575	833	33587	1	1.8	4.6	3	830	1500	1406.4
02/21/17	to	02/27/17	02/28/17	120	2	42695	96	33683	1	0.2	0.6	3	830	1500	1382.5
02/22/17	to	02/28/17	03/01/17	45	2	42740	21	33704	1	0.4	0.2	3	830	1500	1412.5
02/23/17	to	03/01/17	03/02/17	150	2	42890	126	33830	1	0.2	1	3	830	1500	1393.6
02/24/17	to	03/02/17	03/03/17	245	1	43135	233	34063	1	1.2	2.8	3	830	1500	1390.8
02/27/17	to	03/03/17	03/06/17	70	1	43205	58	34121	1	0.4	0.4	3	830	1500	1382.5
02/28/17	to	03/06/17	03/07/17	(140)	2	43065	(164)	33957	1	1.2	3	3	830	1500	1373.1
03/01/17	to	03/07/17	03/08/17	(100)	2	42965	(124)	33833	1	1	0.8	3	830	1500	1364.3
03/02/17	to	03/08/17	03/09/17	(390)	2	42575	(414)	33419	1	1.6	2	3	830	1500	1358.7
03/03/17	to	03/09/17	03/10/17	(130)	2	42445	(154)	33265	1	1	2	3	830	1500	1362.8
03/06/17	to	03/10/17	03/13/17	80	1	42525	68	33333	1	1.2	2	3	830	1500	1369.1
03/07/17	to	03/13/17	03/14/17	(200)	2	42325	(224)	33109	1	1.2	2	3	830	1500	1361.3
03/08/17	to	03/14/17	03/15/17	(5)	2	42320	(29)	33080	1	4.4	1.8	3	830	1500	1381.7
03/09/17	to	03/15/17	03/16/17	(80)	1	42240	(92)	32988	1	6	5.2	3	830	1500	1386.4
03/10/17	to	03/16/17	03/17/17	(530)	2	41710	(554)	32434	1	5.8	5.4	3	830	1500	1390.6
03/13/17	to	03/17/17	03/20/17	70	1	41780	58	32492	1	3.2	4.2	3	830	1500	1382.5
03/14/17	to	03/20/17	03/21/17	2190	1	43970	2178	34670	1	3.6	4.2	3	830	1500	1344.7
03/15/17	to	03/21/17	03/22/17	705	2	44675	681	35351	1	1.4	4	3	830	1500	1342
03/16/17	to	03/22/17	03/23/17	430	1	45105	418	35769	1	1.4	4.4	3	830	1500	1350.9
03/17/17	to	03/23/17	03/24/17	150	2	45255	126	35895	1	1.4	5.8	3	830	1500	1354.8
03/20/17	to	03/24/17	03/27/17	(390)	2	44865	(414)	35481	1	1.2	3.4	3	830	1500	1357.3
03/21/17	to	03/27/17	03/28/17	630	1	45495	618	36099	1	1.6	6	3	830	1500	1364.5
03/22/17	to	03/28/17	03/29/17	430	3	45925	394	36493	1	0.2	4.4	3	830	1500	1371.7
03/23/17	to	03/29/17	03/30/17	170	3	46095	134	36627	1	0.2	4.2	3	830	1500	1381.1
03/24/17	to	03/30/17	03/31/17	175	1	46270	163	36790	1	0.2	1.2	3	830	1500	1384.5
03/27/17	to	03/31/17	04/03/17	(335)	2	45935	(359)	36431	1	0.2	1.2	3	830	1500	1368.6
03/28/17	to	04/03/17	04/04/17	(300)	2	45635	(324)	36107	1	0.2	1	3	830	1500	1368.4
03/29/17	to	04/04/17	04/05/17	655	2	46290	631	36738	1	0.4	0.2	3	830	1500	1347.6
03/30/17	to	04/05/17	04/06/17	(755)	1	45535	(767)	35971	1	4.6	0.8	3	830	1500	1364.5
03/31/17	to	04/06/17	04/07/17	290	1	45825	278	36249	1	2.8	0.8	3	830	1500	1362.2