CS 7641 - Project 6

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SMA - "What is comfortable is rarely profitable."

The Simple Moving Average ("SMA") indicator can be used to gauge a price trend over a given period. Calculating SMA consists of taking the average price over a window of time. Comparing the current price to the SMA measures price divergence relative to the chosen period of time. I leveraged SMA by using the current price's percentage of SMA ("PSMA") to capture the concept of mean reversion. The basic calculations are as follows:

$$\text{SMA}(t, n) = \frac{1}{n}\sum_{i=t}^{t-n} P_i \qquad \text{where } t = \text{start period, } n = \text{lookback, } P = \text{price}$$

$$\text{PSMA}(t, n) = \frac{P_t}{\text{SMA}(t, n)}$$

Using a 20-day window, my manual strategy generates a positive signal for PSMA 1 σ below μ and a negative signal for a PSMA 1 σ above μ. At least 3 consecutive signals were required to trigger a buy or sell signal to provide a margin of safety such that a dip or peak had time to form. Figure 1 shows the indexed price of JPM as well as the indexed SMA over the in-sample period in the top subplot. The bottom subplot provides the relevant standardized PSMA indicator with the constraint levels highlighted by the dashed line. As is the convention in all subsequent plots, blue and black vertical lines denote buy and sell signals, respectively. SMA triggered several buy signals during the late 2008, early 2009 downturn. While the trend over this period was certainly negative, the indicator picked up on periods where the price action proved to be overdone and short-term mean reversion proved a relevant market force.

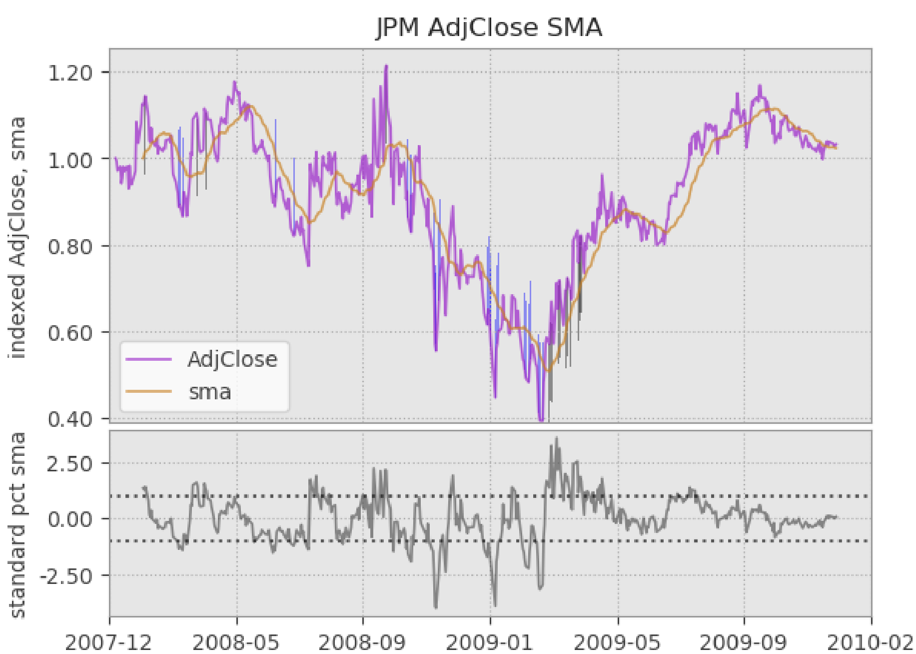

Figure 1: Simple Moving Average indicator over in-sample period

RSI - "No price is too low for a bear or too high for a bull."

The Relative Strength Index ("RSI") is another indicator useful for highlighting setups ripe for mean reversion. The indicator effectively signals overbought and oversold conditions dependent upon the the proportion of average gains to average losses. As outlined in the following equations, RSI consists of a simple proportion of gains to losses when the current period equals the window size and equals a smoothed proportion thereafter.

$$\mathrm{RSI}(t, n) = 1 - \frac{1}{1 + \mathrm{RS}(t, n)} \quad \text{where } t = \text{ start period, } n = \text{lookback}$$

$$RSI(t, n) = \begin{cases} \dfrac{\sum_{i=t}^{n-t} gains_i}{\sum_{i=t}^{n-t} losses_i} & \text{if } t = n \\[2ex] \dfrac{gains_t + 13 \sum_{i=t-1}^{n-t+1} gains_i}{losses_t + 13 \sum_{i=t-1}^{n-t+1} losses_i} & \text{if } t > n \end{cases}$$

I used an RSI value of 0.20 to signal oversold conditions and 0.8 to signal overbought conditions over a window size of 5. The goal of the smaller window size was complement the longer-term nature of the other signals. Although the RSI signal likely generated negative returns over portions of the in-sample period, such as the run up over the mid 2009 period, the metric appropriately highlighted potential mean-reversion setups, which hopefully improves generalization.

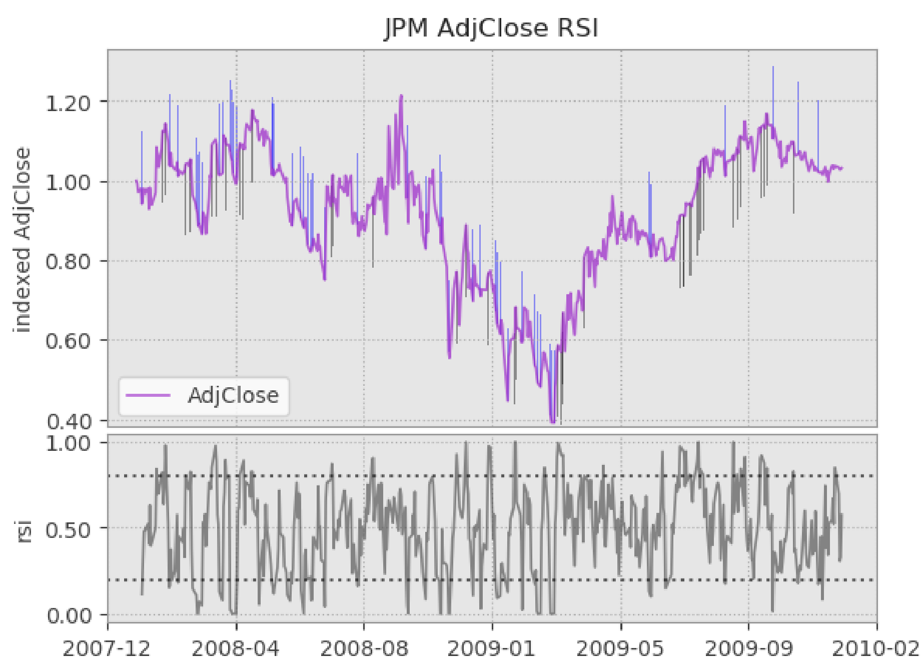

Figure 2: Relative Strength Index indicator over in-sample period

VWPC - "Pigs get fat. Hogs get slaughtered."

In addition to my clear preference towards mean reversion, I wanted to try and use a simple indicator to highlight periods when investor greed could be clouding better judgement. I used the change in the normalized Volume Weighted Price Change ("VWPC") as my greed indicator. The volume weighted price is simply found by comparing the current daily trading value to the lookback period's trading value as follows:

$$\text{VWPC}(t, n) = \frac{V_t P_t}{V_{t-n} P_{t-n}} - 1 \quad \text{for } V = \text{volume},\ P = \text{price},\ t = \text{base},\ n = \text{lookback}$$

Incorporating volume provides insight into market liquidity and depth. A thinly traded market arguably has less relevance than one that is heavily traded since greater liquidity provides price discovery for a larger proportion of the market. While more liquidity typically provides better price transparency, extremely high volume are often indicative of extreme uncertainty. During periods of uncertainty investors have a higher propensity to be guided by emotion, which could result in an overreaction to the current market context. I used a relatively long 30-day window for the VWPC as the basis for the greed signal to mitigate the impact of short-term noise. Because a lack of liquidity is not necessarily indicative of an underlying trend, I set the constraints at 150% and -150% as the respective sell and buy triggers to ensure that only the sell signal would be generated during periods of high volume. Interestingly, from looking at Figure 2, periods of price declines acted as a natural buffer against shorting into a dropping market. The indicator largely highlighted the infamous summer of 2008 as a period ripe for selling.

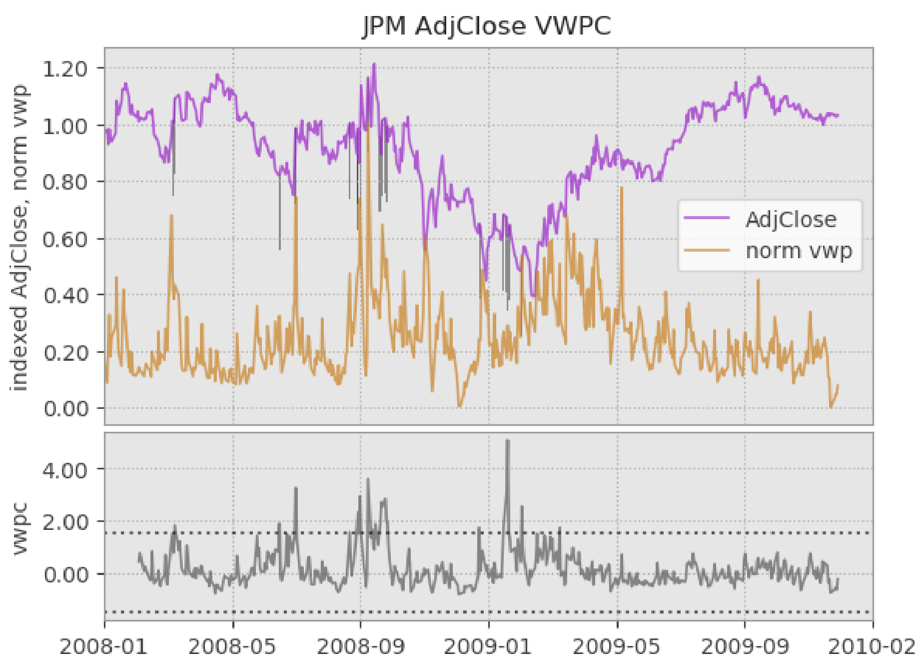

Figure 3: VWPC indicator over in-sample period

1 Strategies

Theoretically Optimal Strategy

The theoretically optimal strategy ("OPT") was simply constructed by comparing the forward and current prices over the in-sample period. If the forward price was above the current price, being long the maximum allowable 1,000 shares was optimal. If the forward price was below the current price, being short the maximum allowable 1,000 shares was optimal. If the current and forward prices were equal or it was the last day of the period, maintaining the current position was optimal.

$$optimal(t) = \begin{cases} 1000 - position_t & \text{if } \frac{P_{t+1}}{P_t} - 1 > 0 \\ -1000 - position_t & \text{if } \frac{P_{t+1}}{P_t} - 1 < 0 \\ 0 & \text{otherwise} \end{cases}$$

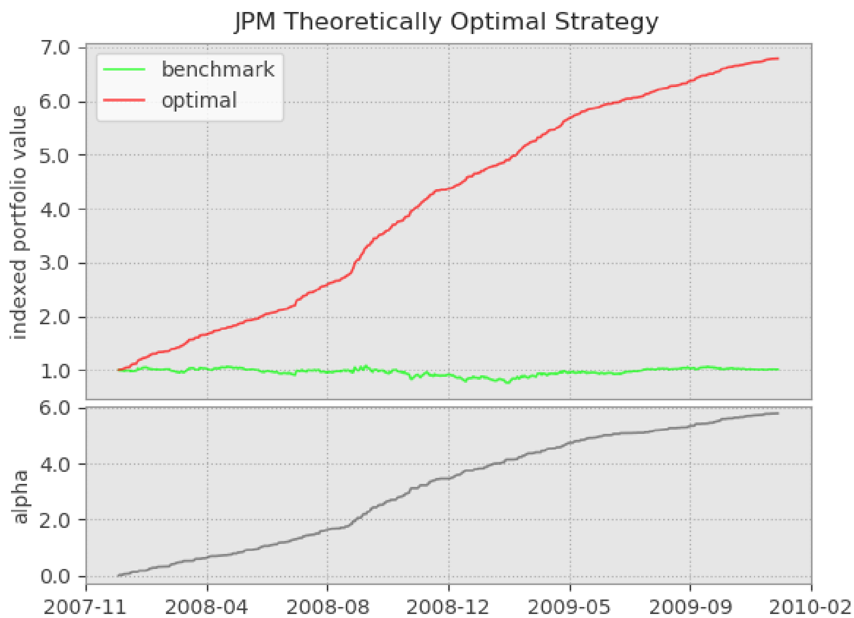

Figure 4: Comparison of theoretically optimal strategy and benchmark; excludes commissions and impact

	cr	std	adr
benchmark	0.0123	0.017	0.00017
optimal	5.7861	0.00455	0.00382

Figure 5: Cumulative, standard deviation, and average returns for theoretically optimal strategy and benchmark; excludes commissions and impact

Manual Strategy Implementation

The manual strategy simply consisted of summing up the aforementioned indicators under the given constraints and checking the resultant value. The sum of the underlying indicators were then clipped to a scale of [-1, 1] to match our maximum short and long position sizes. Summing up the indicators effectively requires a plurality of signals to generate a net positive or negative signal. Hopefully this plurality requirement will help the various signals complement each other to generate only high conviction signals as opposed to relying on any one specific signal. I also did not want to weight the various signals differently since I have absolutely no view on which indicator should be more meaningful over a given period. While this is a clear drawback, I believe the overall benefit of using more of an ensemble approach outweighs the negative of simplistically assuming a uniform weighting. Importantly, I attempted to restrict my risk exposure to high conviction setups by focusing the manual strategy on the impact of a change in the underlying signals as opposed to the absolute value at any given time. I achieved this by using the change in the total indicator value, $\Delta I = I(t) - I(t-1)$, as the basis for buying or selling JPM. A positive ΔI triggered a buy signal whereas a negative ΔI triggered a sell signal. If the current holdings already consisted of the maximum long or short exposure then the position remained unchanged. A more formal summary of the approach is as follows:

$$
\begin{aligned}
\text{manual}(t) &= \begin{cases} 1000 & \text{if } \Delta I > 0 \text{ and } position_t < 1000 \\ -1000 & \text{if } \Delta I < 0 \text{ and } position_t > -1000 \\ 0 & \text{otherwise} \end{cases} \\
\Delta I &= I(t) - I(t-1) \\
I(t) &= I_{PSMA}(t, 20) + I_{RSI}(t, 5) + I_{VWPC}(t, 30) \quad \text{where } I(t) \in [-1, 1] \\
I_{PSMA}(t, n) &= \begin{cases} 1 & \text{if PSMA}(t, n) > \mu_{PSMA} + \sigma_{PSMA} \,\forall\, t \in \{t_{-2}, t_{-1}, t_0\} \\ -1 & \text{if PSMA}(t, n) < \mu_{PSMA} - \sigma_{PSMA} \,\forall\, t \in \{t_{-2}, t_{-1}, t_0\} \\ 0 & \text{otherwise} \end{cases} \\
I_{RSI}(t, n) &= \begin{cases} 1 & \text{if RSI}(t, n) < 0.2 \\ -1 & \text{if RSI}(t, n) > 0.8 \\ 0 & \text{otherwise} \end{cases} \\
I_{VWPC}(t, n) &= \begin{cases} 1 & \text{if VWPC}(t, n) < -1.5 \\ -1 & \text{if VWPC}(t, n) > 1.5 \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
$$

Manual Strategy In-Sample Results

The manual strategy significantly outperformed the benchmark over the in-sample period, generating materially higher cumulative returns and average daily returns while also having lower standard deviation of daily returns. The lower standard deviation of daily returns, analogous to volatility, is attributable to the limited daily market exposure of the manual JPM strategy. By intentionally limiting the long or short hold period the strategy avoided unnecessary market risk over the in-sample period. To be clear, this is certainly not guaranteed and to a large extent the result of overfitting the strategy to the in-sample period. The strategy seemed to markedly outperform the benchmark during the tumultuous, trending periods. This is likely because the SMA was able to identify departures from the trend while the RSI was able to highlight near-term potential overreactions. It would be interesting to see how the strategy performs during less volatile periods. My suspicion is that the results would be far less robust since the strategy is basically just a giant mean reversion play.

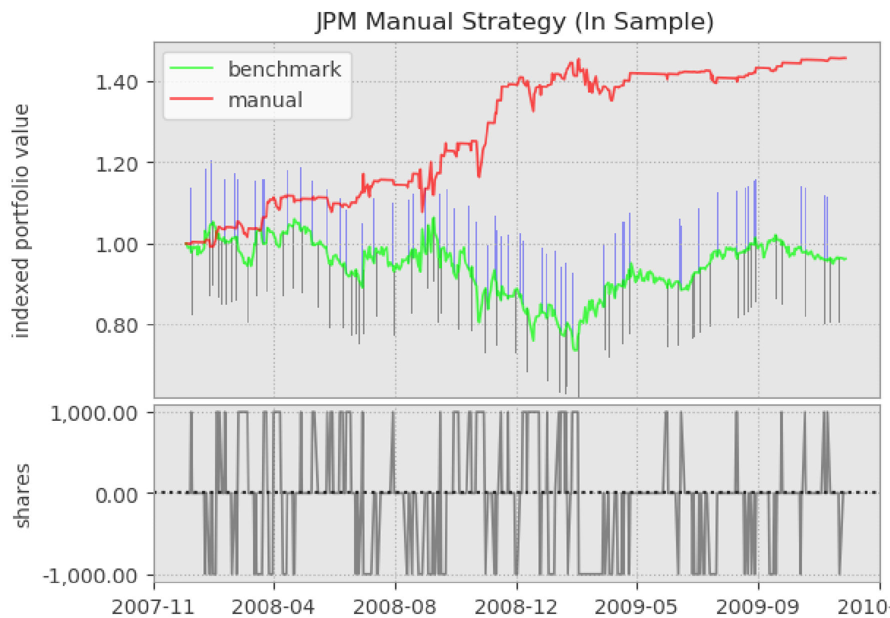

Figure 6: Manual strategy performance over in-sample period; includes $9.95 commissions and 0.001 impact

	cr	std	adr
benchmark	-0.03787	0.01744	7e-05
manual	0.45668	0.01008	0.0008

Figure 7: In-sample period cumulative returns, standard deviation of daily returns, and average daily returns for manual strategy and benchmark; includes $9.95 commissions and 0.001 impact

Manual Strategy Out-Of-Sample Results

Although the manual strategy again outperformed the benchmark across the cumulative return, average daily returns, and standard deviation of daily returns metrics over the out-of-sample period, the relative outperformance was muted as compared with the in-sample outperformance. This is to be expected since I specifically selected the indicators and tuned the constraints, window sizes, and frequency requirements based on the in-sample period while ignoring out-of-sample performance. Interestingly, the manual strategy performed best over periods where a clear trend emerged such as over the mid to late 2011 timeframe. As previously mentioned, this was likely because the SMA was able to highlight departures from the longer-term trend which was further supported by short-term moves identified by the RSI signal. The VWPC signal may have also helped generate alpha during the late 2011 period when the benchmark rose significantly on high volume in a short period of time. Prior to the late 2011 downturn, the strategy mitigated excessive risk taking by limiting the duration of market exposure. The strategy did not generate significant alpha over 2010, but also did not have a significant drawdown, enabling it to live to fight another day.

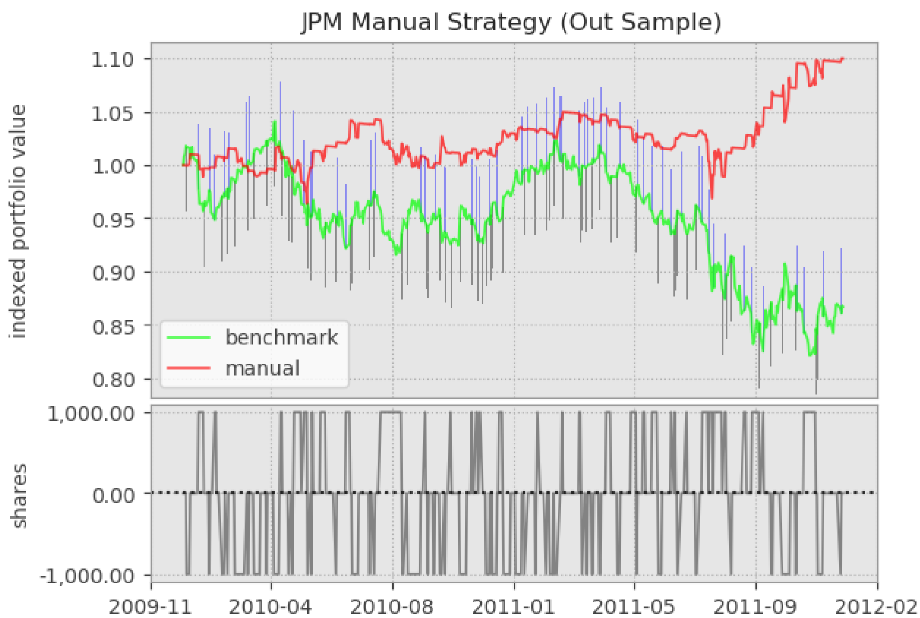

Figure 8: Manual strategy performance over out-of-sample period; includes $9.95 commissions and 0.001 impact

	cr	std	adr
benchmark	-0.13352	0.00877	-0.00025
manual	0.09956	0.00557	0.0002

Figure 9: Out-of-sample period cumulative returns, standard deviation of daily returns, and average daily returns for manual strategy and benchmark; includes $9.95 commissions and 0.001 impact