USING CORRELATIONS AND VOLATILITY TO CLASSIFY MARKET RISK REGIMES

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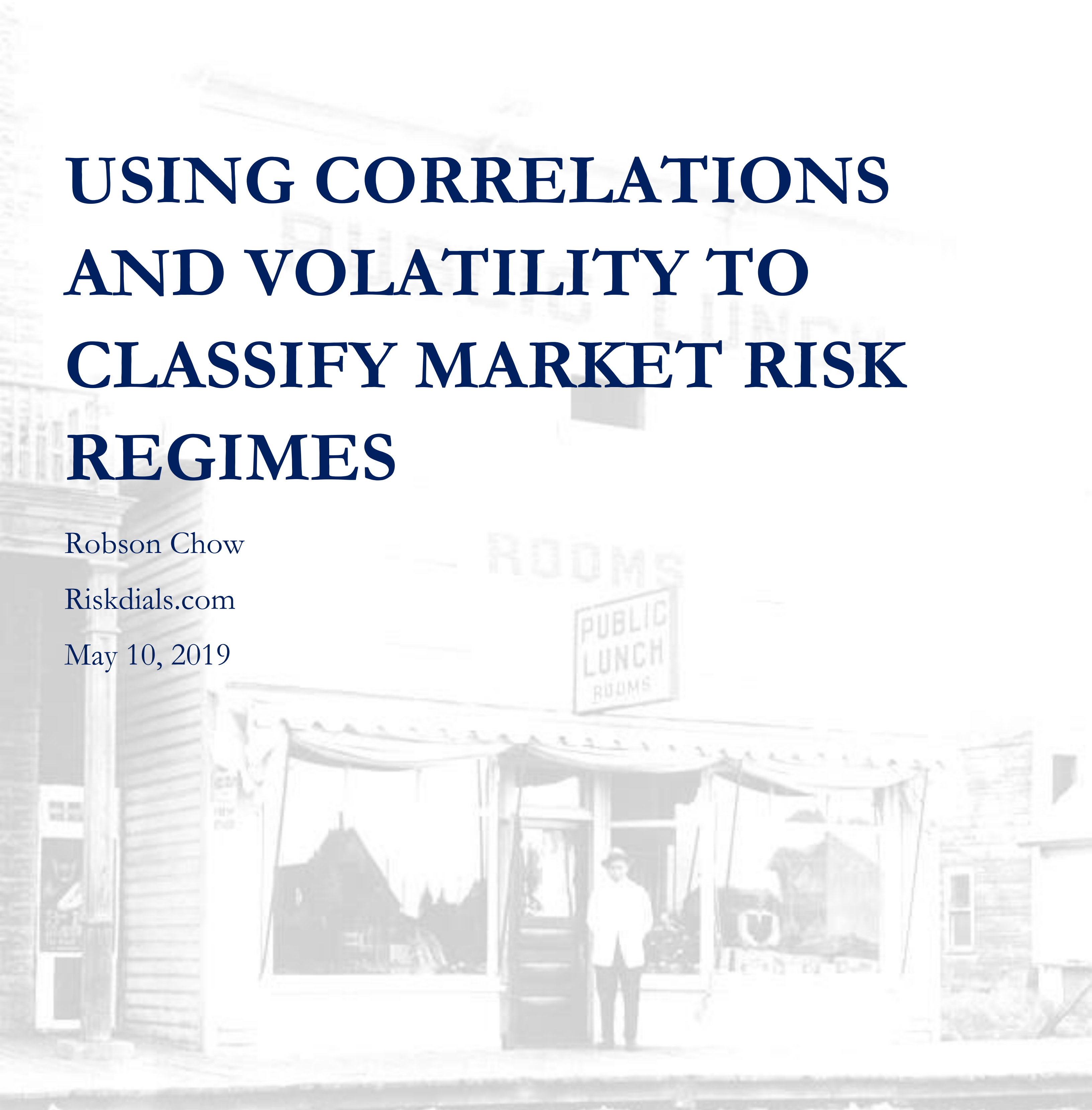


USING CORRELATIONS AND VOLATILITY TO CLASSIFY MARKET RISK REGIMES

In this post we explore how we use correlations and volatility to determine market risk and return profiles. To do this, we focus on US SP500 Sector Correlations, showing that low correlation regimes exhibit low volatility, while high correlation regimes exhibit high volatility. First, we provide background on why we believe Correlations are important and what this tells us about investor behavior.

Career Limiting Move Losses, Value at Risk and J.P. Morgan's Risk Metrics

Until the mid 1990's risk management was relatively unheard of amongst large corporations and there was a flurry of companies reporting outsized "CLM" (Career Limiting Move) losses.

In February of 1993, Showa Shell Sekiyu oil company of Japan lost USD $1.05 billion from FX trading. In December of that same year MG refining and Marketing of Metallgesellschaft AG, a German company lost USD $1.3 billion from botched hedging of oil sales. In 1994, Kashima Oil of Japan lost USD $1.5b from FX trading. Similarly in 1994, the "OC", California's Orange County lost USD $1.7 billion on repos. Some incredible losses indeed, but perhaps the most bewildering of all was the collapse of Barings Bank caused by rogue trader Nick Leeson (Nick personally lost USD $1.4 billion and caused the collapse of the +200 year old Bank (founded in 1762).

So… what do all these losses have to do with correlations and volatility!?!?. This string of CLM losses created a significant spike in interest in risk management throughout industry and were partially responsible for the public release of J.P Morgan's service Risk Metrics. Risk Metrics allowed JPM's subscribers to upload their positions to compatible service providers, who would then calculate a one day 95th percentile loss for the subscriber. This was metric is known as Value at Risk. To translate into simple English, Risk Metrics would calculate the one-day loss which a trader, firm etc. could expect ***just*** 5% of the time. **The main inputs to J.P. Morgan's Risk Metrics subscriber service were correlations and volatilities.**

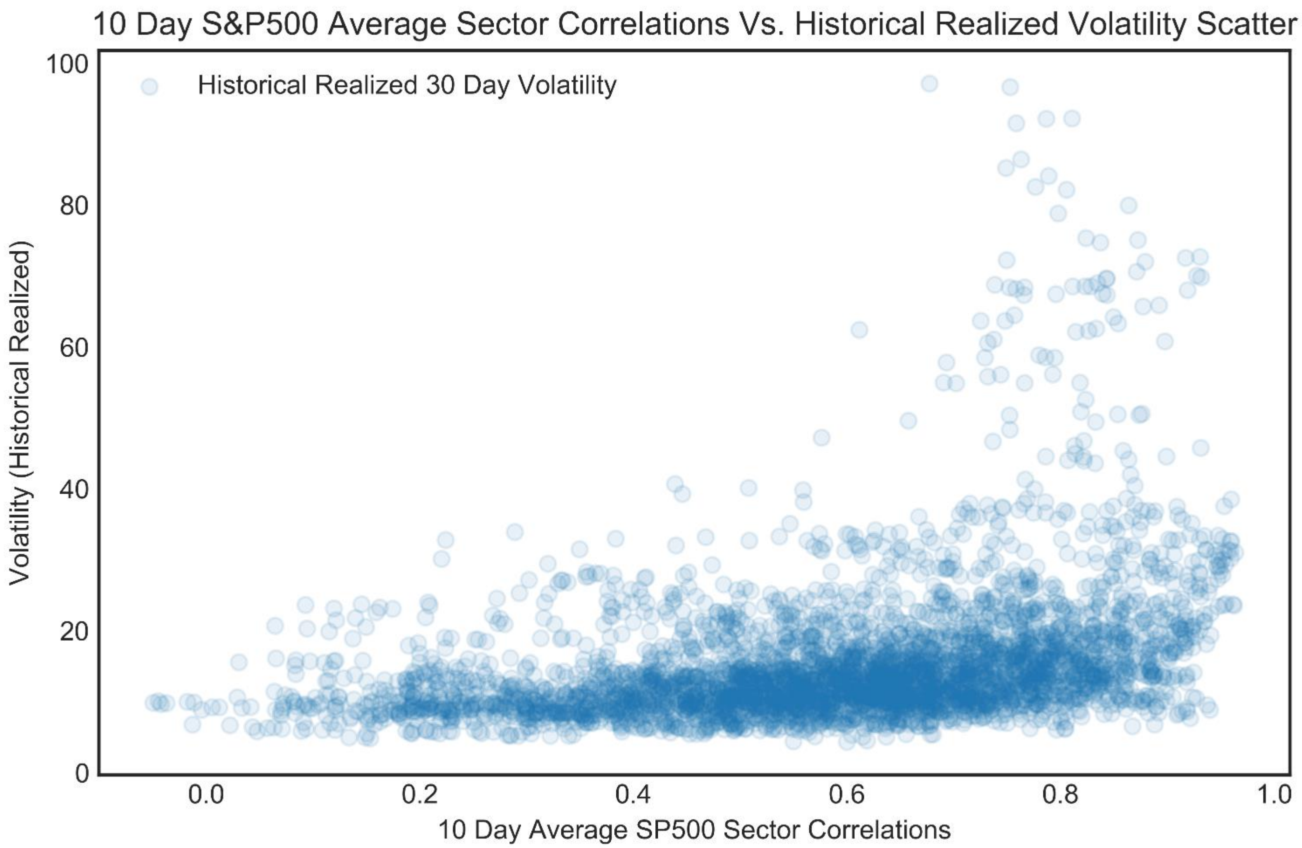
Correlations and Investor Behavior

When writing this post, we momentarily pondered whether correlations could be interpreted as a distillation of investor sentiment, to which we immediately concluded, absolutely. In a Bloomberg interview from 2017, Dr. Brett Steenbarger who has worked with some of the world's largest hedge funds, notes that, *"...the greatest challenge facing traders, investors, investment firms is the correlation among their performers. People are looking at the same things, putting on the same trades, developing the same investment ideas."* So what does this mean and how does this translate to the public markets as a whole? Let's let Dr. Brett answer that one as well, *"…we tend to get high correlations during and immediately after periods of market correction, as traders and investors bail out of risk assets and then back into them. At relative price peaks in markets, especially when volatility has been lower, the average intermarket correlations have been lower. This is a rough look at an important phenomenon, as it captures portfolio-related decision making across a broad range of assets. Only large institutions can affect these correlations, which makes the average correlation a useful tool in gauging the sentiment of active money managers."* Great, now we know exactly how and why correlations are a distillation of investor sentiment, let's transition into the analysis.

S&P500 Sector Correlations and Market Regimes

Now, if we think about the average market index and the constituents that drive its performance, we can determine our own Value at Risk metric. To do this for the S&P500 we use the individual sector constituents. In particular, we calculate average ten-day S&P500 sector correlations on a daily basis. This allows us to determine SPY price ranges (aka VaR) as well as to classify market regimes and risk / return profiles. This calculation methodology is dubbed a *"historical simulation"*. Below we show that low correlation regimes exhibit low volatility, while high correlation regimes exhibit high volatility.

Figure 1: Sector Correlations Vs. Volatility



We present our walk forward analysis by comparing SPY 50 day returns against various correlation ranges. First we summarize the data into a table, then we present the data graphically, and finally drill down into what it all means.

Table 1: Average Correlation Summary Statistics

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Correlation	Mean 50 Day Return	Median 50 Day Return	Average if Up	Average if Down	Max Drawup 50 Days	Max Drawdown 50 Days	Max Drawup	Max Drawdown
>.90	4.93%	5.94%	6.76%	-3.14%	15.64%	-7.83%	23.88%	-13.36%
.75 - 1.0	3.24%	4.17%	6.58%	-5.95%	33.78%	-29.71%	36.51%	-37.80%
.50 - .75	1.02%	1.90%	4.39%	-5.18%	28.85%	-39.89%	32.70%	-40.16%
.25 - .50	0.98%	2.20%	3.67%	-5.06%	11.32%	-35.51%	12.34%	-35.52%
<.25	1.45%	2.92%	4.14%	-5.72%	10.94%	-25.10%	11.75%	-35.25%
<.10	3.22%	3.22%	4.79%	-4.58%	10.94%	-14.00%	11.75%	-14.00%
SPY Any Time	1.57%	2.47%	4.76%	-5.34%	33.78%	-39.89%	36.51%	-40.16%

Figure 2: Ten Day Correlations Between .75,1.0

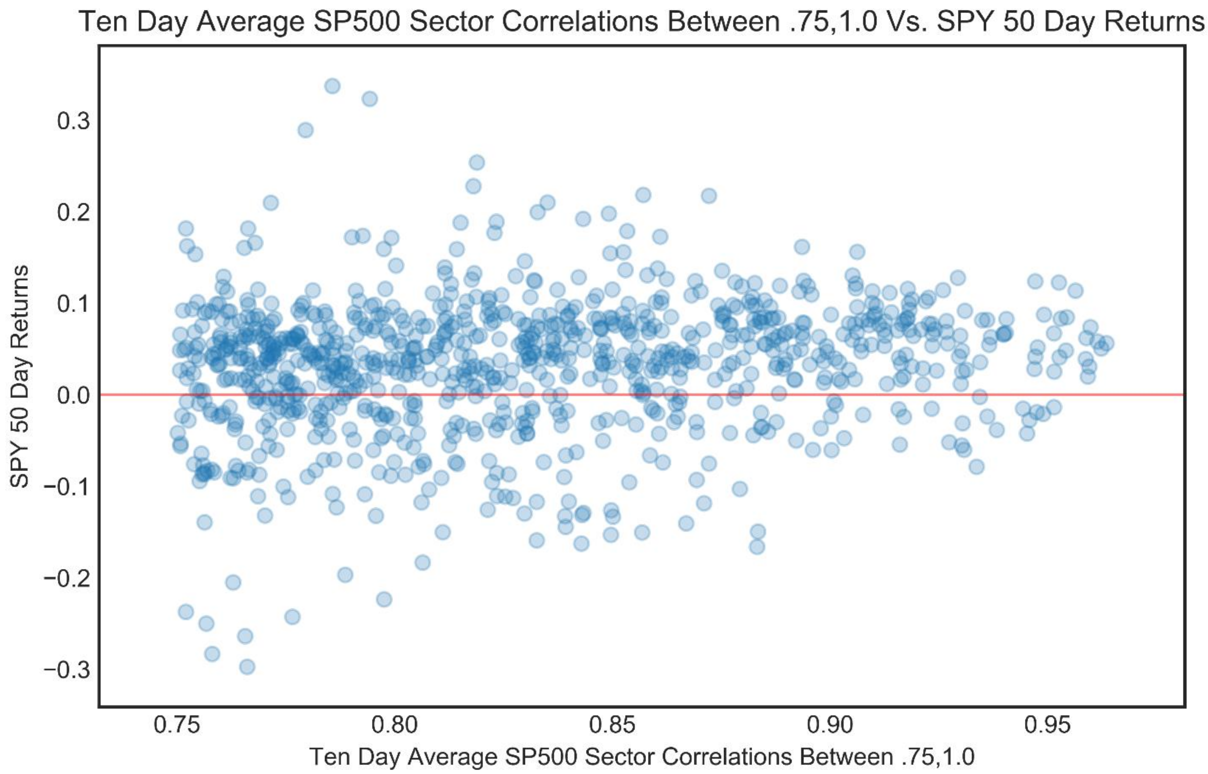


Figure 3: Ten Day Correlations Between .50,.75

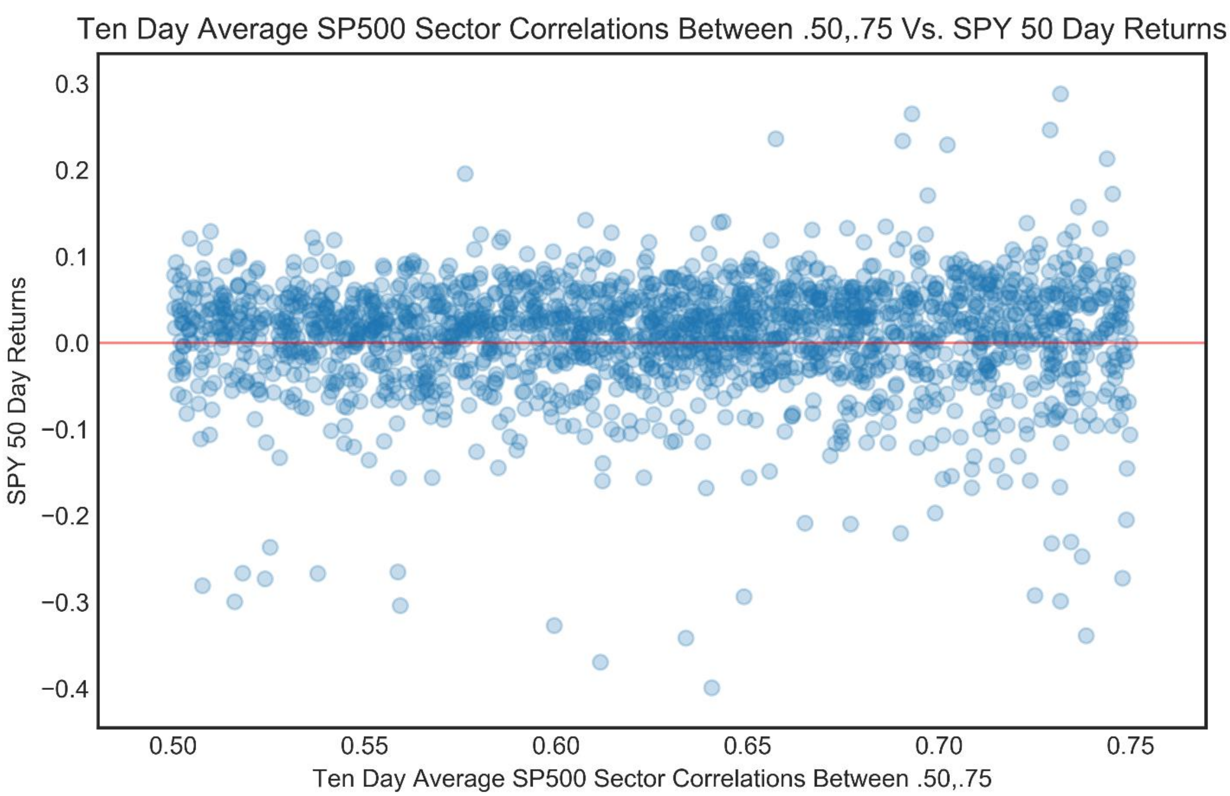


Figure 4: Ten Day Correlations Between .25,.50

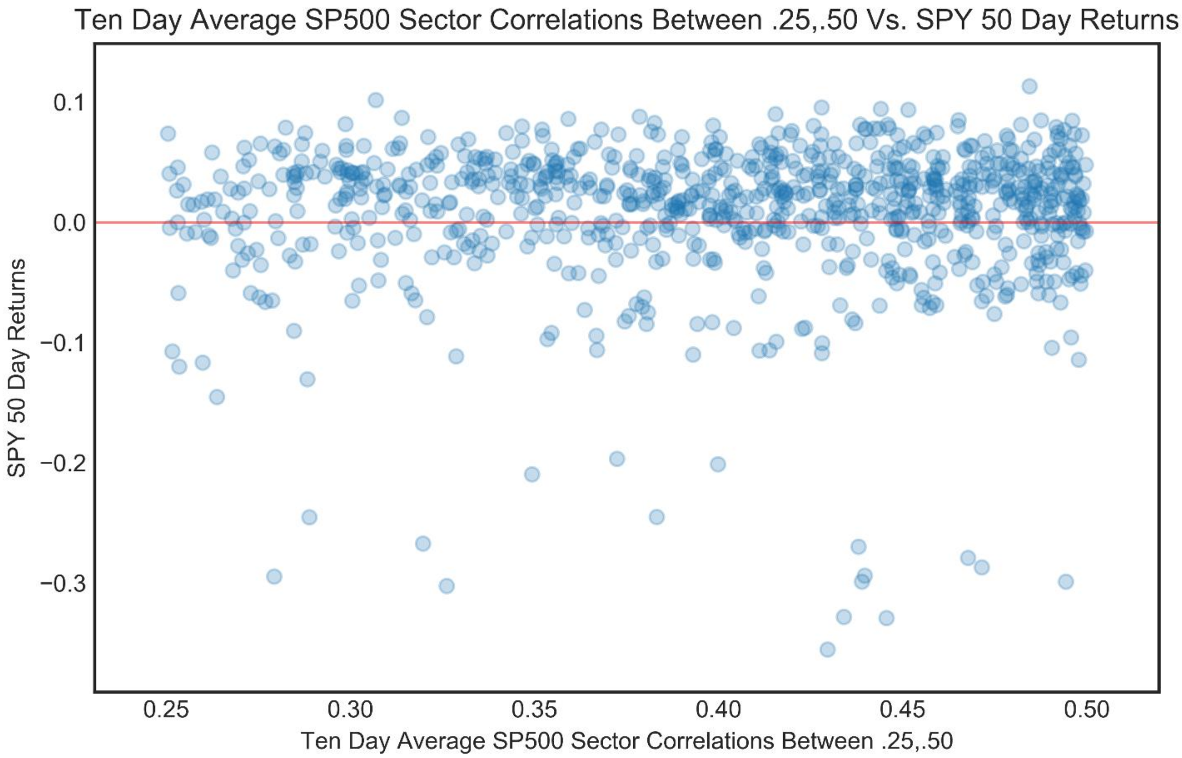
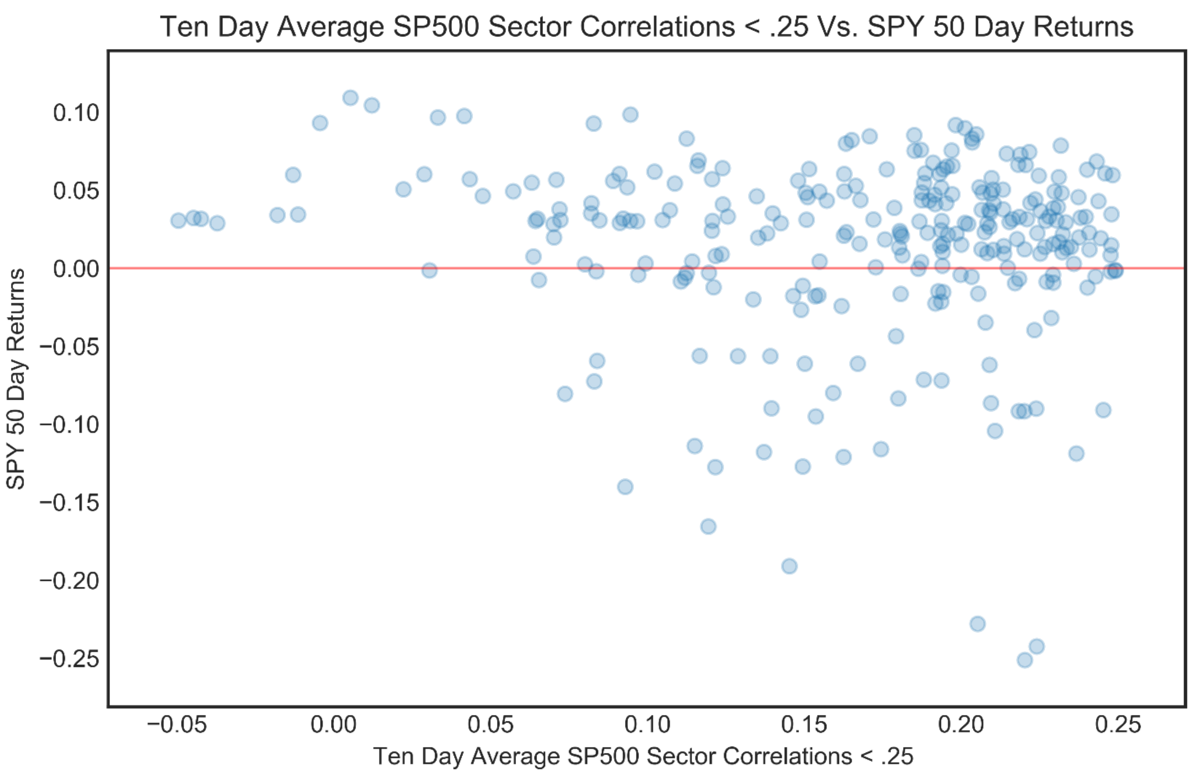


Figure 5: Ten Day Correlations < .25



What do we gather visually from these figures?

1. First, we notice that higher correlations are much more prevalent than lower correlations. Average S&P 500 Sector Correlations are higher than .5 about 70% of the time.
2. Second, we notice the prevalence of both positive and negative returns is also much higher during higher correlation periods
3. Third we notice that, during correlation extremes ie. <.1 or >.9 (and also summarized in the first table);
    a. Drawdowns have been more limited than in other regimes.
    b. Mean and median returns are higher than in other regimes.

In the two figures below we present the two most extreme correlation regimes and their corresponding dates for your perusal.

Figure 6: Ten Day Correlations > .90

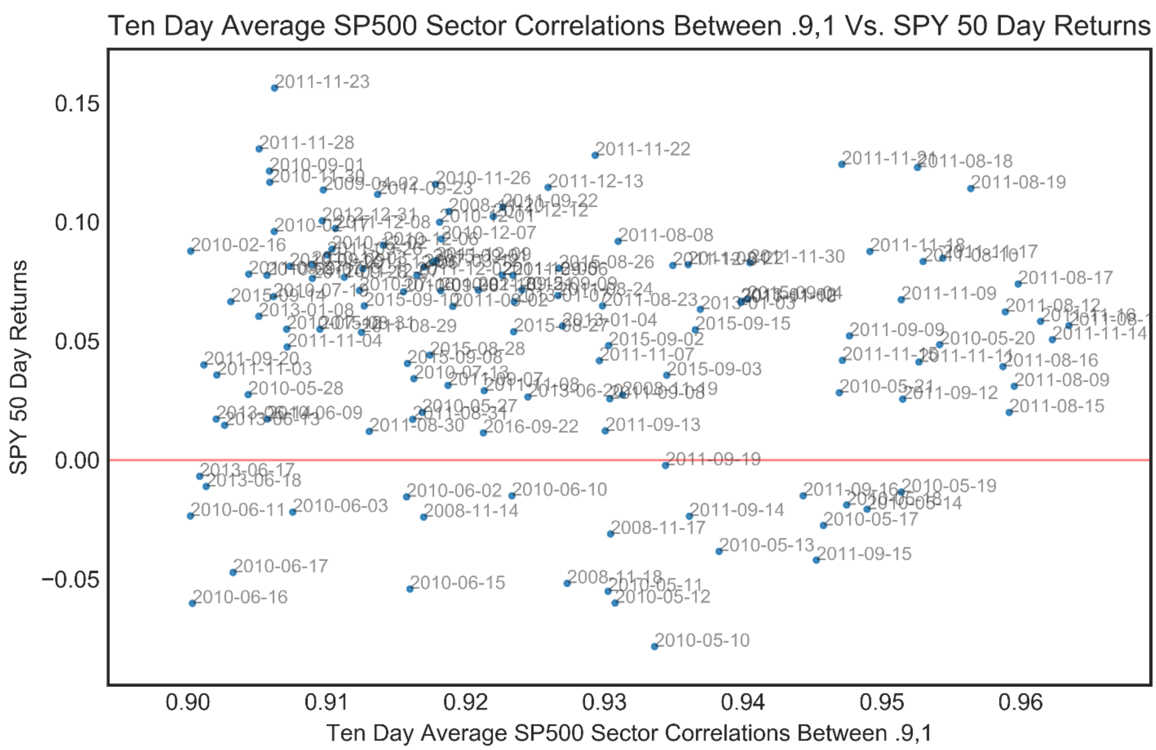
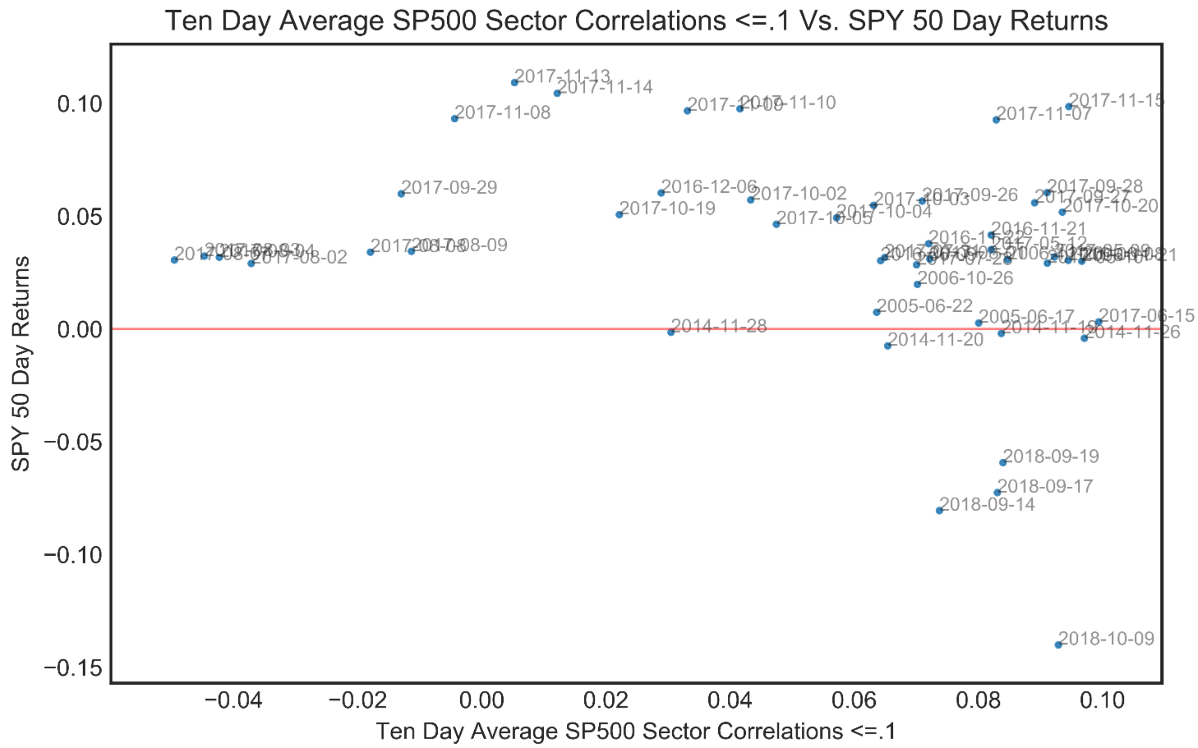


Figure 7: Ten Day Correlations < .10



What it All Means

Our analysis has broken out correlations into 6 regimes and shows that the most interesting and the rarest regimes (<=.10 or >=.90) offer strong risk/reward characteristics. We have done this work because we believe it to be particularly important for investors (and traders) to understand what kind of risk and return profile he/she is facing on any given day, and what that regime translates into for expected S&P500 price ranges. This knowledge will allow the investor (and trader) to make better informed decisions and manage their risk based on data and facts rather than emotion and opinion.

REFERENCES

Value-at-Risk Theory and Practice, Glyn A. Holton

www.Traderfeed.blogspot.com