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Subject: A Quantamental Approach to Navigating Financial Crises and Large Market Dislocations

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Funds that fail to beat their benchmarks quickly go extinct. Generating alpha is an extraordinarily difficult task. One that is becoming increasingly difficult, a reality illustrated by deteriorating hedge fund returns. **Find alpha or die** is the stark new reality for every portfolio manager. At the same time, we are living through a technology driven data explosion. In the world's 2.5 billion gigabytes of data, Wall Street sees its savior. The prevailing belief is that this data — and the predictive power it promises — is the most powerful alpha source to emerge in the last quarter century. The $3 trillion hedge fund industry is currently betting its future on it.

This sentiment is especially true as markets enter a period of unprecedented volatility and uncertainty as the world grapples with the fallout of the pandemic. It does not take a crystal ball to anticipate a storm on the horizon. A market once thought "wacky" has tipped into full-blown madness. How we navigate through this storm could very well determine the fate of some funds, perhaps even the firm as a whole. To this end, I am proposing a quantamental approach to help us navigate current and future crises.

To be clear: models are not magic, they have their limitations and are only as good as their assumptions and the quality of the data they ingest. Every model, regardless of complexity, should under-go sufficient levels of scrutiny. Models may appear predictive when they are not and can lose predictive power as market conditions change. It is therefore in the firm's best interest for us to reserve belief in the model until it passes the appropriate checks-and-balances. In the remaining sections of this memo, I do my best to take this "black box" and make it as transparent as possible without losing the forest for the trees.

1 Motivation

With oceans of information and only so much time to investigate fundamentals before pulling the trigger on an investment decision, where we look for opportunities and risk is of critical importance. It is becoming increasingly easy to lose the forest through the trees, especially on particularly demanding days. Running a lean shop has its disadvantages and this is one of them. While for the foreseeable future machines are unlikely to master the fundamentals, they are particularly good at sifting through large amounts of data and finding patterns otherwise invisible to the analyst. Models can provide clues the analyst can not see and the analyst can provide intuition and expertise the models can not comprehend. The idea is this: build a model that detects anomalous increases in correlation that most often precede large market dislocations. The anomalies offer an executable signal that is ultimately at the discretion of individual desks to further investigate.

In the following section, I walk you through the model, the assumptions I make, the promising preliminary results I obtain, and the conclusions I make.

Figure 1: Fraction of DJA stocks with a pairwise correlation above 0.3

2 Market Sociology

Suppose we survey every investor on the planet. Assuming everyone has access to the same N pieces of information, we could ask: given the nth piece, are you a bear or a bull? Market behavior is often considered to reflect external economic news, though empirical evidence has challenged this connection [1]. Indeed, it is ultimately the investor's internal outlook and biases that determine how they answer the question. They can imagine a threat when there is none and ignore one when there is. What is more, investors can and often will, ignore accumulating evidence of an economic crisis — until they don't — and panic.

In sociology [2–5], panic has been defined as a collective flight from a real or imagined threat. In economics, bank runs occur at least in part because of the risk to the individual from the bank run itself—and may be triggered by predisposing conditions, external (perhaps catastrophic) events, or even randomly [6, 7]. Although empirical studies of panic are difficult, efforts to distinguish endogenously (self-generated) and exogenous (externally-generated) market panics from oscillations of market indices have met with some success [8–10], though the conclusions have been debated [11–14]. The literature generally uses the volatility and the correlation between asset prices to characterize risk [15–19]. These measures are sensitive to the magnitude of price movement and therefore increase dramatically when there is a market crash.

This proposal is not radically different from what has been achieved in the literature. By making precise measurements of correlations between asset prices and the volatility of those correlations, we can paint a more complete picture of the market and look for early warning signals of extreme volatility and market dislocations. The reality of this approach is that correlations are non-stationary (they change in time) and are known to harbor non-linear effects. As such, instead of using Pearson's correlation, I compute Székely's correlation (which measures both linear and non-linear associations in the data).

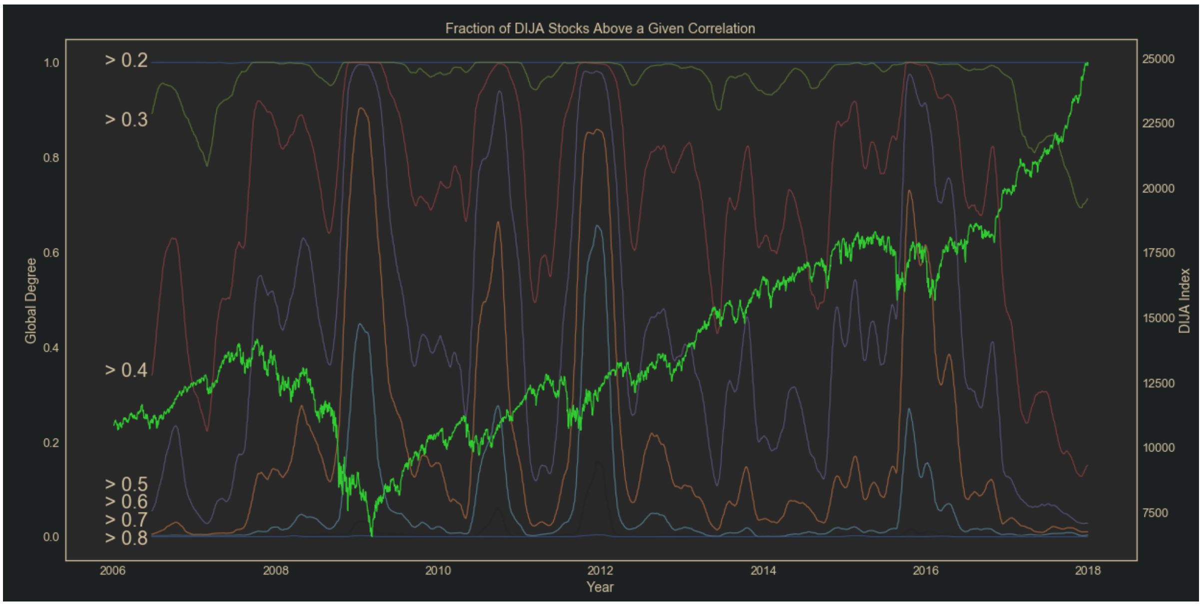

Figure 2: Fraction of DJA stocks with a pairwise correlation above 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8.

2.1 Preliminary Results

Figure 1. is a chart of the fraction of DJA stocks with a pairwise correlation above 0.3 from 2006 to 2018. For most of 2006 the indicator decreased then reached a local minimum on 2007-02-08, the same day HSBC warned bad debt provisions for 2006 would be 20% higher than expected. After HSBC's warning, and over the course of four months, the indicator increased to a local maximum on 2007-06-21. A day earlier Merrill Lynch seized $800M in assets from Bear Stern's hedge funds as they imploded. Another indicator to observe is the volatility of correlations. In the bottom panel of Figure 1. is a chart of the volatility of correlations above 0.3. Upon inspection, it would appear correlation volatility precedes price volatility, indicating these signals posses predictive power.

There is nothing special about setting the correlation threshold to 0.3. A better picture of how correlations ebb-and-flow in the DJA is revealed by Figure 2., where we look at the fraction of stocks above several thresholds. Clearly, during a downturn correlations increase dramatically. But what is intriguing, as it would appear, is the relatively slow migration from weak to strong correlations leading up to downturns. This slow migration is especially true leading up to the 2008 Global Financial Crises (GFC) where correlations slowly crept up throughout 2007 and skyrocketed in October of 2008.

2.2 Detecting Anomalous Increases in Market Correlations

The final step is to use machine learning (ML) to classify whether or not an increase in correlation is anomalous. I avoid making any assumptions of the underlying distribution of the data and consult the literature for the algorithm with the best track record for similar tasks. The algorithm works like this: it partitions the data points into two groups based on how similar they are to each other. The data points least similar to the rest of the crowd are labeled anomalies.

Running the correlation volatility through the ML algorithm yields ten anomalies over twelve years. Six of the anomalies precede the 2008 GFC, with dates as follows: 2006-10-23, 2007-06-20, 2008-01-22, 2008-08-07, 2008-09-29, and 2008-10-10. The largest anomaly occurred

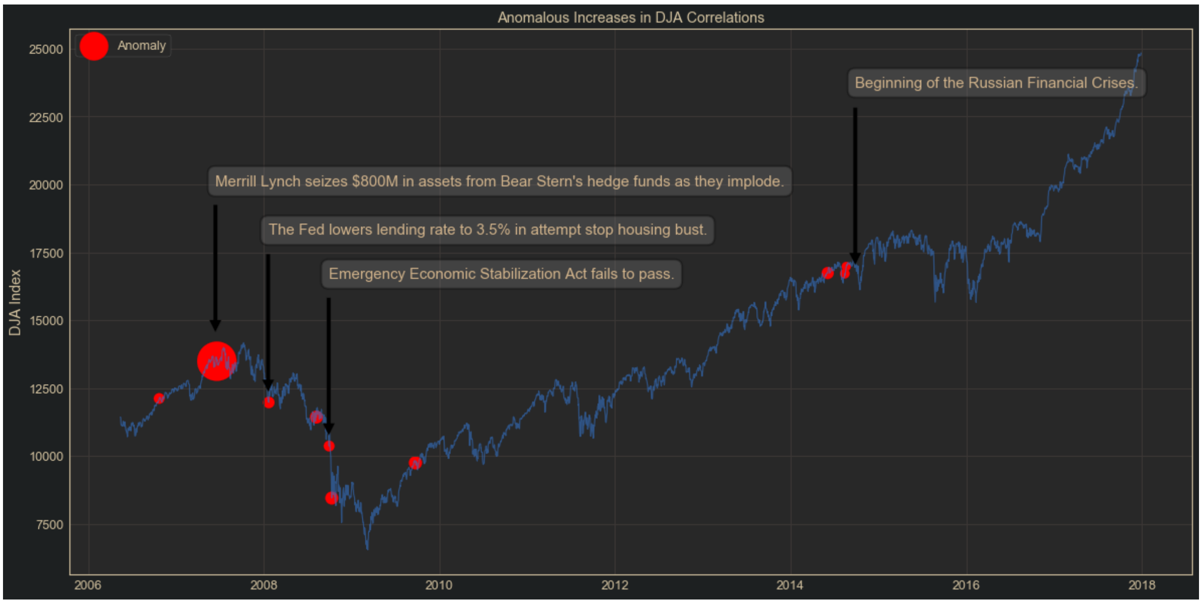

Figure 3: Anomalous increases in correlation in the DJA index.

on 2007-06-20, the same day Merrill Lynch seized $800M in assets from Bear Stern's hedge funds as the funds implode. The following anomaly occurred the same day the Fed lowered the lending rate to 3.5% in attempt to prevent the collapse of the housing market. The anomalies on 2014-06-04, 2014-08-14, and 2014-08-20 preceded the crash in oil prices followed by the Russian Financial Crises. With the exception of the false-positive anomaly detected on 2009-09-23, the model, as it would appear, works as intended.

2.3 Conclusion

Given the preliminary results the approach looks promising. However, to ensure we do not fool ourselves there are checks-and-balances the model ought to pass before giving it serious consideration. First and foremost, I need to systemically identify and remove any statistical biases that may have crept into the analysis and increase the data volume. Second, I need to confirm the anomalies we are looking at are a genuine signal and not noise. Finally, I need to find a way of quantifying the predictive power of the model without starring at charts. These tests can all be accomplished in a reasonable period of time with a conservative estimate of two-to-three weeks, as I have conducted the necessary research to confidently move forward.

2.4 References

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