Managed Futures Return Dispersion: A Review

Kathryn M. Kaminski, Ph.D., CAIA®
Chief Research Strategist,
Portfolio Manager

Ying Yang, M.F.E.
Junior Research Scientist

October 2020

Introduction

Correlation does not imply causation. In the same way, it is important to remember that high correlation does not imply similar returns. In the Managed Futures space, most trend-following returns are roughly 60-80% correlated over the long term. Yet, in a given year or given time period, returns can be noticeably different. This occurs because even for two highly-correlated assets, there is still substantial **return dispersion,** or difference in return. It can be viewed either as ***pairwise* return dispersion** (one manager vs. another) or ***cross-sectional* return dispersion** (across a group of managers). In Managed Futures, we often like to say it is easy to replicate trend-following correlation but difficult to explicitly replicate returns. Consider a simple moving average cross-over system: it will certainly be highly correlated to the SG Trend index and many other managers' returns, but it would be naïve to think that it would have the same returns as either the index or any individual manager. Many investors have undoubtedly performed this experiment with limited success.

Volatility abounds in 2020

2020 has certainly been a volatile year, and it isn't over yet. Figure 1 plots the realized cumulative returns, realized volatility, and realized correlation of ten Managed Futures funds from the SG Mutual Fund Index during the first three quarters of 2020. At a first glance, cumulative returns varied more widely in Q1 and Q3 than in Q2, while realized volatility seems to be reducing from Q1 to Q3. In terms of inter-manager correlation, Q1 was a period where the managers in this set seemed to be the most different from each other.

Figure 1: 2020 returns, volatility, and pairwise correlation by quarter for ten Managed Futures mutual funds in the SG Managed Futures Mutual Fund Index. The quarterly return is aggregated with compounding from daily returns. The annualized volatility and pairwise correlation are estimated on a daily frequency for each quarter. Past performance is not necessarily indicative of future results. Data source: Bloomberg.

Given the range of outcomes we saw in 2020, particularly in Q1 2020, we decided to perform a 5-year review of return dispersion for trend-following strategies to put 2020 into perspective. To provide a baseline set of managers with daily available returns, we use the set of U.S. '40-Act Managed Futures managers in the SG Mutual Fund Index.[1] Although Figure 1 used cumulative returns to demonstrate the variation in returns we have seen this year during three different periods, in the remaining portion of this note, for simplicity, we use annualized versions of return dispersion measurements to avoid the complications of cumulative or compounding returns. First, we consider *pairwise* return dispersion by considering the theoretical implications of highly-correlated pairs of returns. This allows us to compare theoretical expectations with the realized pairwise return dispersion we have seen both this year and since 2015. Second, we turn to *cross-sectional* measures of return dispersion and examine how returns have varied across the set of managers. Using several metrics for measuring cross-sectional return dispersion, we consider how returns have varied in the group over time. We also consider a few key potential drivers of differences in return, based on both system construction (trend speed, asset allocation) and market environments (market volatility).

Quantifying pairwise return dispersion for highly-correlated portfolios

A trend is a trend is a trend—or is it? Because trend-following managers follow similar trends in global markets, their returns may also be highly correlated (as mentioned above, this correlation can be as high as 60-80% across individual managers, with even higher correlations to the relevant indices). However, we also know that systems and methods may vary somewhat from manager to manager. In practice, measurement windows, signal speeds, risk allocation, and overall risk targeting methodologies can vary greatly, leading to potential return dispersion. To put this simply, the trends are the same but how you capture them can vary substantially. For investors, this concept must be frustrating from time to time. Consider two managers, Manager X and Manager Y, that both follow a similar strategy with correlation defined as (ρ). If we make a few simplifying assumptions, we can find a closed-form expression for the difference between the return series of the two managers, or the level of *pairwise* **return dispersion**. We assume the return series for both managers have the same volatility and expected return, but this result can be extended. In this case, we use the following terms to approximate pairwise return dispersion.[2]

$$E[|r_X - r_Y|] = \frac{2\sigma\sqrt{1-\rho}}{\sqrt{\pi}}$$

In this example, the expected return difference decreases when correlation increases (as shown in Figure 2 below). At a 0.7 correlation level, we should expect an average return difference of about 7.5% between the two managers. That is to say, given the same level of

---

[1] After September 2020 the SG Mutual Fund Index will be discontinued. There is substantial overlap between this Index and the SG Trend Index, with the exception that the SG Mutual Fund Index contains only funds with daily available returns. We use the set of managers in this Index for a representative sample of the space.
[2] Greyserman and Kaminski 2014 (Chapter 11).

risk, we should expect the typical annual difference between managers to be on the order of 7.5% on average. If *pairwise* return dispersion between the two managers is much higher and potentially biased in some way, either their volatilities or the overall expected returns for the two managers are not the same. To determine this would require further analysis.

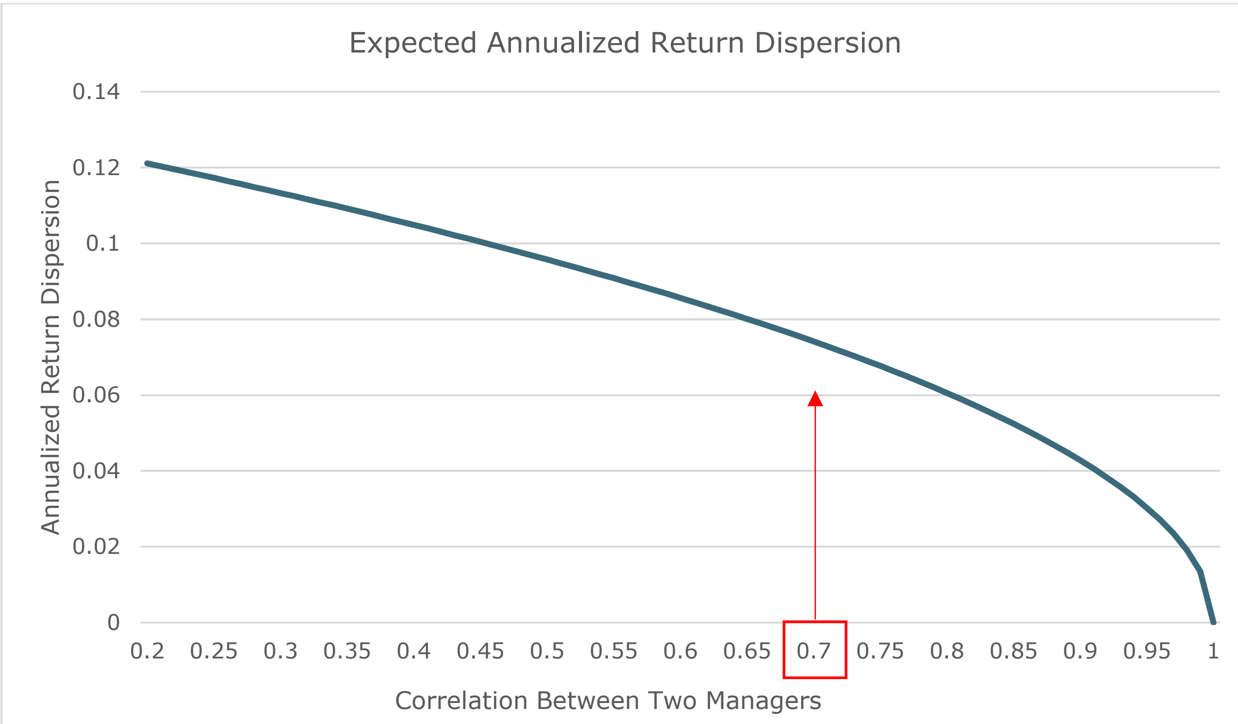


Figure 2: Assuming two random variables have the same mean and variance, we can approximate the return dispersion from the index by the equation above. This graph demonstrates the level of expected return dispersion as a function of the correlation between the two assets. Source: Greyserman and Kaminski 2014.

Using the SG Mutual Fund Index as a proxy for a benchmark set of ’40-Act Mutual Fund Managed Futures managers, we can consider actual empirical values for pairwise return dispersion across this group of ten managers with data since 2015 and compare them to expected estimates generated using the aforementioned equation. We first compute pairwise correlations between the managers to demonstrate how correlated they are from 2015 to present. Figure 3 plots the realized correlation of all combinations of two-manager pairs. In terms of correlation, these managers seem very similar over the entire sample period from 2015 to Q3 2020.

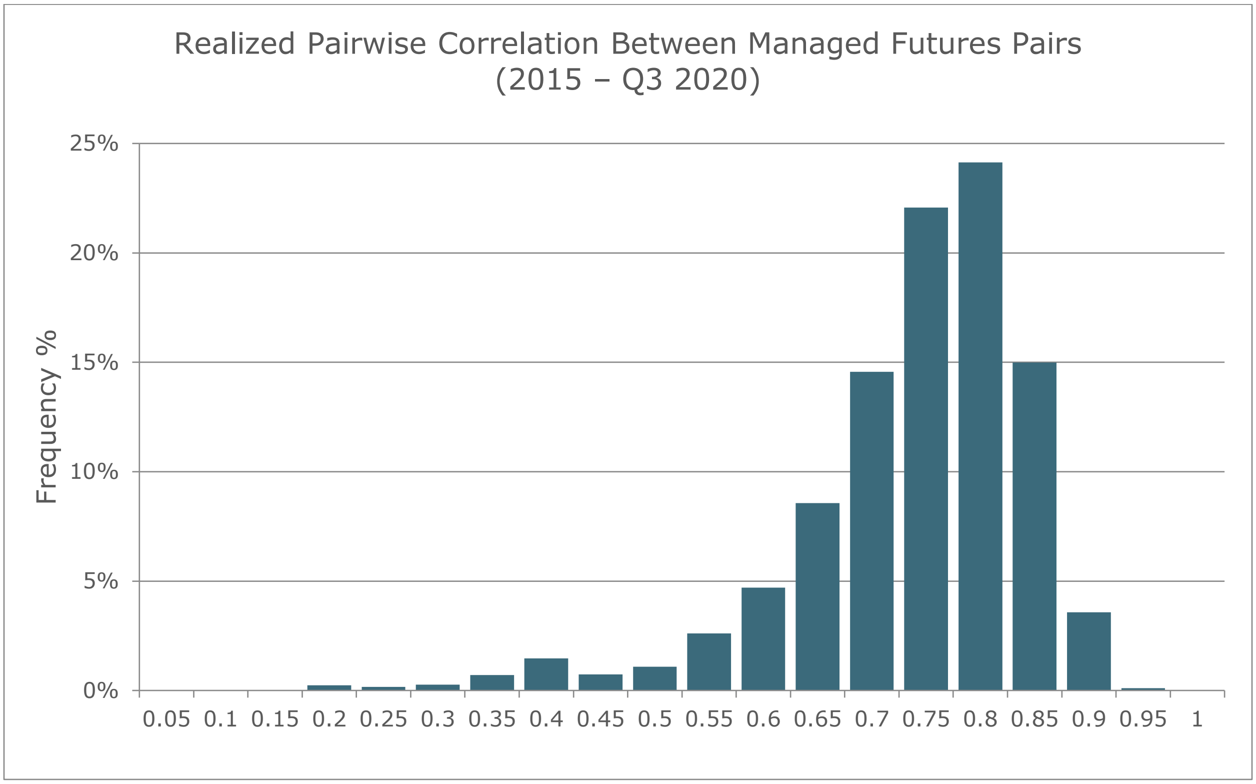
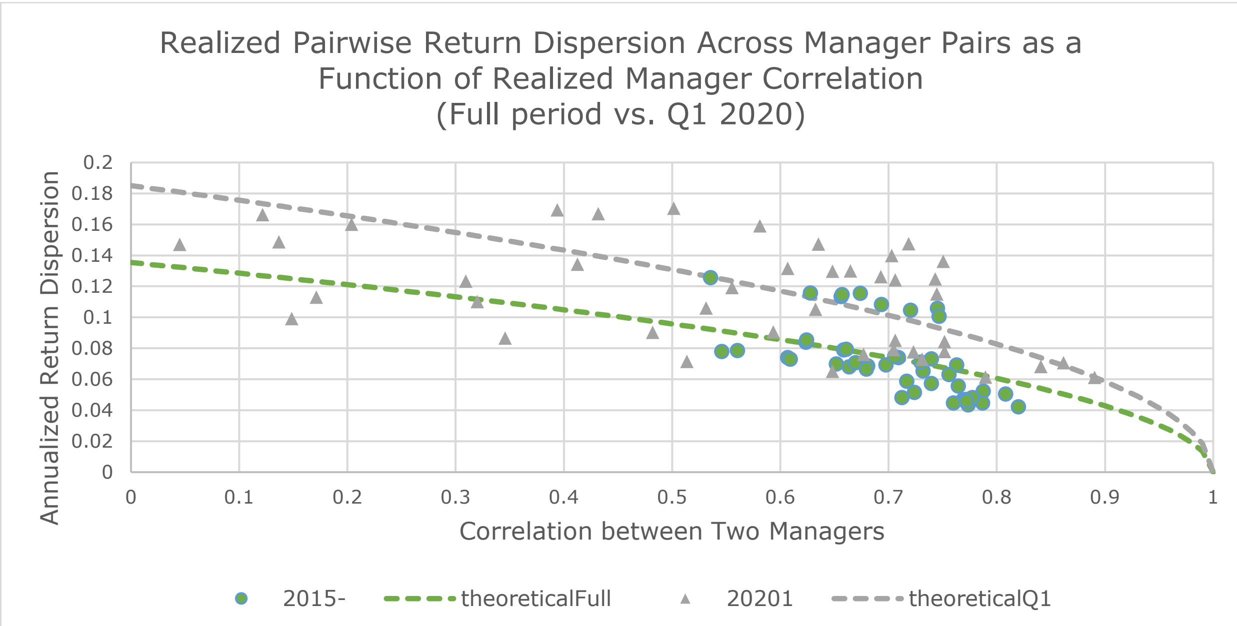


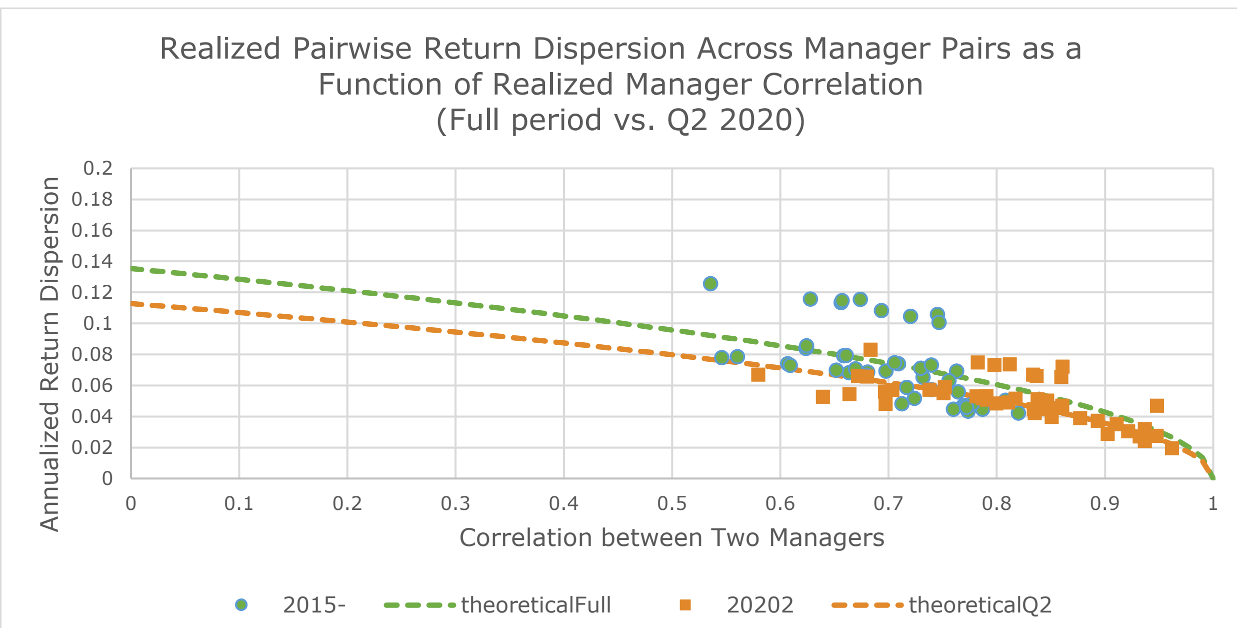
Figure 3: Realized pairwise correlation between each pair of two managers in the SG Mutual Fund Index. These correlations are measured for each pair of managers using rolling one year windows for the time period of 2015 to Q3 2020. The histogram then shows all possible pairs over a range of one year horizons during that period. Correlations are calculated using rolling daily data. Data source: Bloomberg.

Next we calculate the realized average pairwise return dispersion over the entire period and in each quarter of 2020. The values are annualized for simplicity in interpretation. The next figure plots the realized pairwise return dispersion during each quarter in 2020 and during the entire period (2015 to Q3 2020) and, for comparison, compares them to the corresponding theoretical return dispersion[3]. The green-blue circles represent the entire period, 2015 to present, and they are repeated in each figure for comparison for each quarter of 2020. To clarify, each figure has empirically measured values of pairwise return dispersion plotted relative to the realized correlation during the same period comparing both a recent quarter of 2020 and the entire period. We note that the realized values for return dispersion are roughly in line with our theoretical estimates. When we take a closer look at the three time periods, we also note that realized *pairwise* return dispersion in Q1 2020 was higher than the entire period and in some cases even higher than what might be expected for the average realized volatility of managers in the group in Q1 2020. Empirically, this suggests that this time period had temporarily higher manager volatility with even higher pairwise manager return dispersion. Given the market environment and the elevated market volatility during that

[3] Using the equation from the prior section, the theoretical value uses the average level of realized manager volatility during each period as the volatility assumption to calculate expected pairwise return dispersion as a function of correlation. Note that realized pairwise return dispersion is plotted against the realized pairwise correlation for each pair of managers, and the theoretical return dispersion is plotted as a function of possible correlation values.

period, this is not too surprising. For comparison, Q2 was a period with higher pairwise manager correlation, lower realized manager volatility, and lower *pairwise* return dispersion. One thing is clear from this graph: when realized market volatility is higher, managers seem to realize higher volatility and *pairwise* return dispersion is also higher.





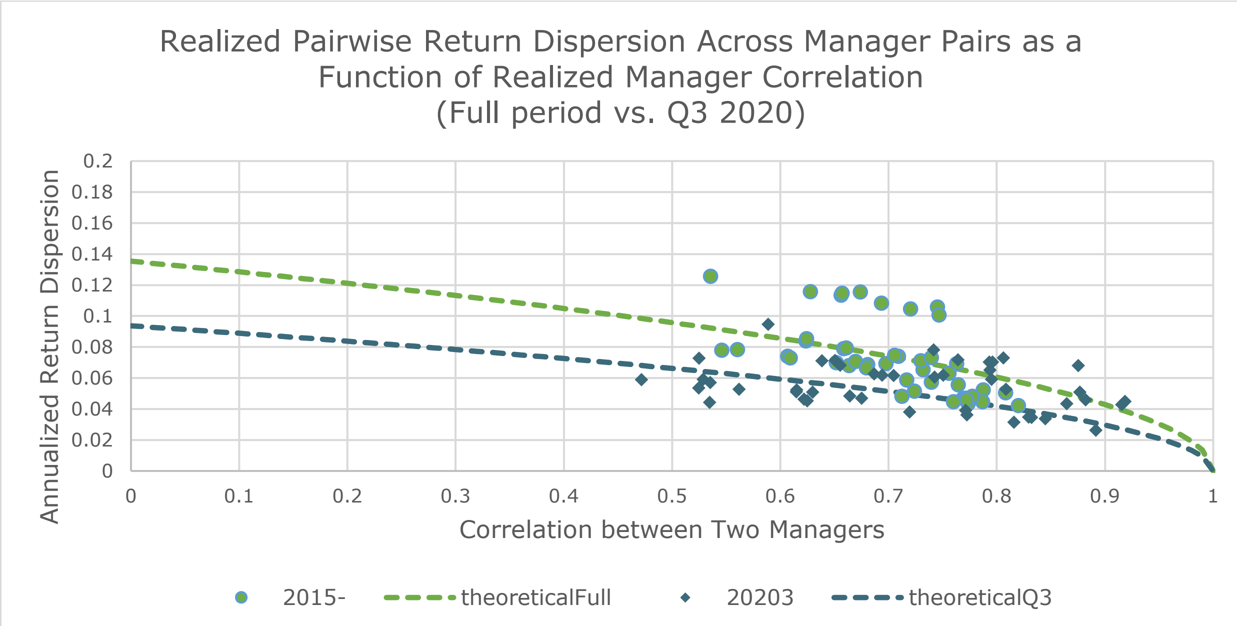


Figure 4: Annualized return dispersion for all pairs of managers in the SG Mutual Fund Index using data from 2015 to present. These values are not scaled to the same volatility to illustrate the volatility impact. The theoretical dispersion line uses the average manager volatility for each quarter in 2020. Data source: Bloomberg.

Cross-Sectional Return Dispersion

Given that *pairwise* return dispersion seems to vary over time, next we consider how returns vary across a basket of managers, or *cross-sectional* return dispersion. Unfortunately, there is no closed form analytic solution for cross-sectional return dispersion, but we can measure it empirically over time using various metrics, such as standard deviation or measuring ranges. In this paper, we consider the interquartile range (IQR), or mid 25-75 percentile of returns, the standard deviation of returns, and the total range (maximum minus minimum).[4] The total range is a worst-case vs. best-case scenario for an investor. Figure 5 plots measures of *cross-sectional* return dispersion from 2015 to Q3 2020. From this figure, we can see that the middle range of managers experiences some fluctuations in return dispersion. However, the total range, which includes large outliers, experiences much higher return dispersion. For example, using quarterly measures of return dispersion, in Q1 2020 there was almost a 14.6% difference between the best performing and worst performing manager in the group.

[4] Using IQR on a small set of only ten managers, this tends to be the mid six-to-eight managers excluding roughly the one to two worst and the one to two best managers. Source: Greyserman and Kaminski (2014) Chapter 11.

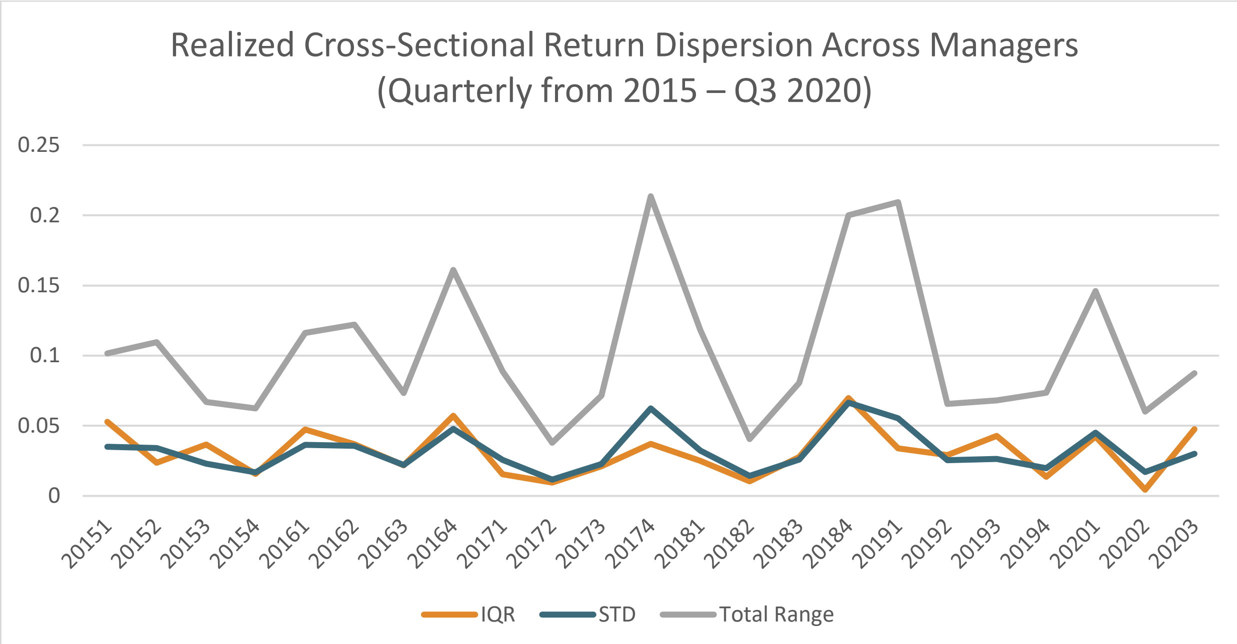


Figure 5: Quarterly return dispersion for ten '40-Act Mutual Fund managers from 2015 to Q3 2020. Return dispersion is measured using three methods: IQR (25-75 percentiles), standard deviation, and total range (max-min). Data source: Bloomberg.

As we can see from Figure 5, periods with greater return dispersion could potentially be periods with heightened volatility or other significant shifts in markets. These shifts might drive differences in how different trend systems would be positioned and thus create very different returns. To examine this, Figure 6 plots the total range (max – min) on a quarterly basis versus market volatility as measured by average volatility of all asset classes.

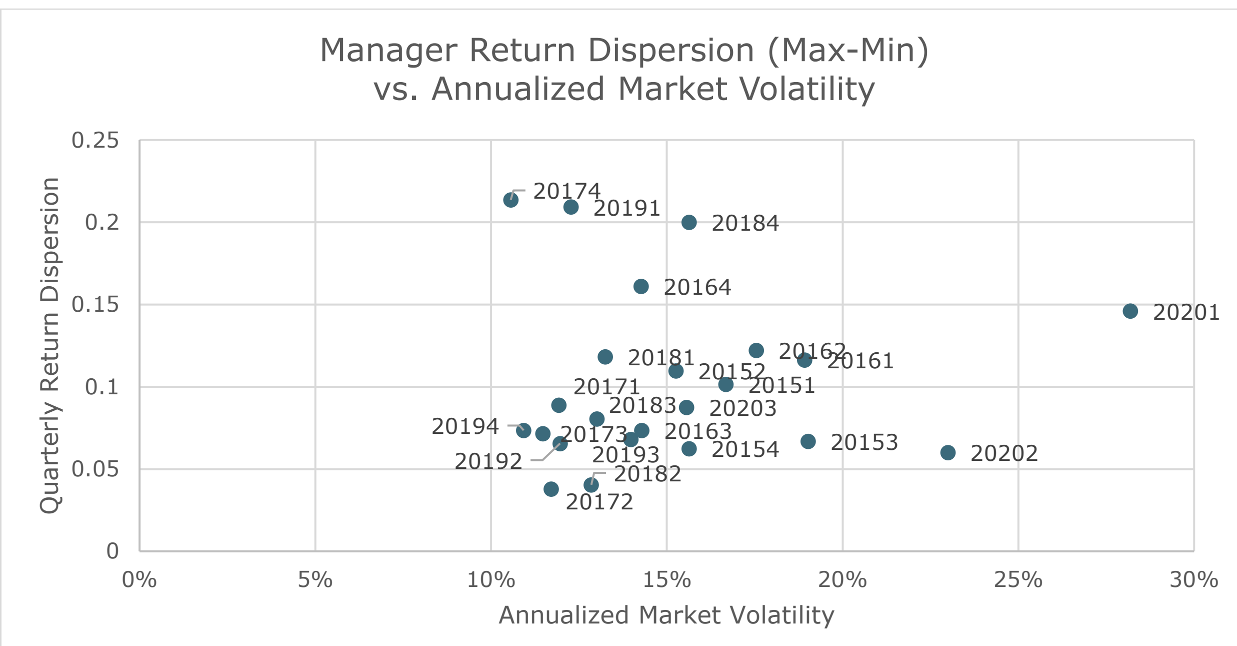


Figure 6: Quarterly return dispersion mapping total range (maximum minus minimum) versus market volatility (as measured by average volatility of all asset classes). Data source: Bloomberg.

From Figure 6, we can see that an elevated volatility environment can be associated with high *cross-sectional* return dispersion for certain periods (e.g., Q1 2020, Q4 2018), but it is less useful at explaining high return dispersion in Q4 2017, Q1 2019, or Q4 2016. This suggests that market volatility might be one factor that could create return dispersion, but there could also be others.

Examining Potential Drivers of Return Dispersion

In this section, we consider three potential drivers for *cross-sectional* return dispersion: trend speed, asset allocation, and market volatility. The first two potential drivers we can examine as part of trend-following system construction; the third is dictated by the market environment, not the trend-following system construction itself. For the first two, we consider a range of parameters for a hypothetical trend-following system and how different trend-following systems might behave from 2015 to Q3 2020. For trend speeds, we examine different trend systems ranging from faster ones with 20-day windows to slower ones with 200-day windows. For the asset allocation choices, we range allocations by asset class.[5] For both trend speed and market allocation, we consider the simulated performance across many different parameter choices and examine how different parameters may drive cross-sectional return dispersion. In this case, we take the group of returns and measure the IQR (interquartile range) as a proxy for cross-sectional return dispersion. For the final and third potential driver of return dispersion, market volatility is measured using the average realized volatility of a range of asset classes (equities, fixed income, currencies, and commodities). We note that both system construction approaches result in an estimated IQR using historical simulation, but market volatility is simply a product of the market environment at that time.

Given the range of outcomes for trend speed (IQR), market allocation (IQR), and market volatility, we standardize the values across time in order to compare this with the measured realized cross-sectional return dispersion (IQR) for ten Managed Futures managers in Figure 7 and Figure 8. From Figure 7, we can see that during certain periods differences in trend speed may drive *cross-sectional* return dispersion (for example, Q1 2020, Q4 2016, Q4 2018, and Q3 2015). Anecdotally, these periods seem to be periods where strong shorter-term trends seem to be very different from the longer-term trends. In addition, trend allocations to different asset classes seem to be more relevant drivers of cross-sectional return dispersion during certain periods (for example, in Q1 2020 with big equity moves, Q3 2019 with big bond moves, Q4 2017 with big equity moves, and Q1 2015 with big commodity moves).

[5] Consistent with Greyserman and Kaminski (2014) Chapter 11.

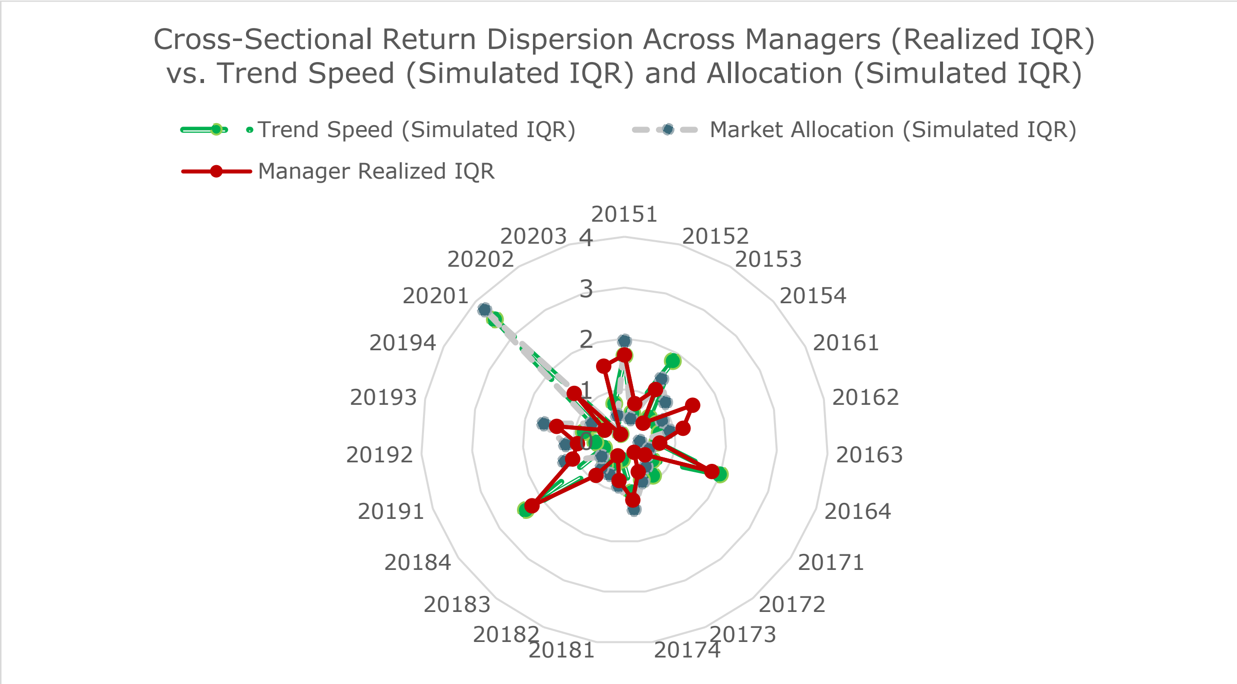


Figure 7: Quarterly cross-sectional return dispersion using standardized realized IQR for ten Managed Futures managers versus the simulated IQR for a range of hypothetical trend systems with different trend speeds and the simulated IQR from a range of hypothetical trend systems with varying market asset class allocations from 2015 to Q3 2020. The method for measuring trend speed and allocation IQR is consistent with the approach from Greyserman and Kaminski (2014) Chapter 11. Data source: Bloomberg.

Figure 7 focused on system construction and different choices that might work differently in varying market environments using simulated returns to examine the potential impact on realized return dispersion. Figure 8 focuses more on overall market conditions by measuring both realized average manager volatility and market volatility across asset classes. An interesting finding from this graph is that market volatility seems to have a less profound impact on return dispersion overall. From the trend-following perspective, this indicates that most managers are relatively successful at managing volatility, except for in the extreme cases like Q1 2020. Periods where manager volatility is higher include Q1 2020, Q1 2018, and Q4 2018. Each of these were periods of short reversals, especially in equity markets. From Figure 7 and Figure 8, we can see that Q1 2020 had the highest volatility for both managers and the markets themselves as well as one of the highest potentials for differences based on trend speed and allocation. Yet the overall return dispersion for the mid-range of managers was high but not one of the highest historically. The higher cross-sectional return dispersion for the mid-range of managers was the highest in Q4 2018 and in Q4 2016. For each of these periods, trend speed and asset allocation both seem to be the likely drivers of return dispersion, not volatility.

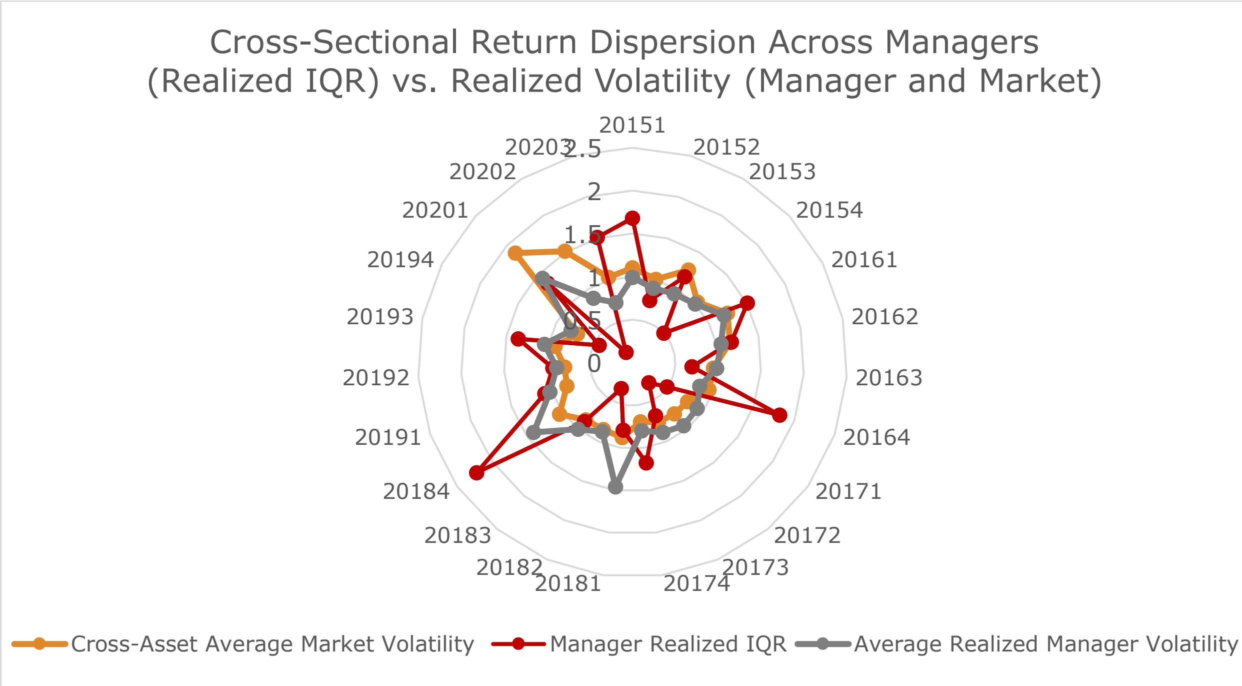


Figure 8: Quarterly cross-sectional return dispersion using standardized realized IQR for ten Managed Future managers versus both average manager realized volatility and average market volatility from 2015 to Q3 2020. The average market volatility is averaged over the four asset classes (equities, fixed income, currencies, and commodities) and manager volatility is averaged over the group of ten managers for each quarter. Data source: Bloomberg.

Summary

Trend-following systems are designed to change with changing market environments and Q1 2020 was certainly a wild ride. When it was all over, the wide-ranging results led investors to wonder if this level of return dispersion was normal or simply to be expected in a period with such high volatility. In this note, we found that Q1 2020 was a period with heightened return dispersion no matter how you measure it (in pairs or as a group). However, the level of return dispersion was in line with historical experience and expectations.

References

- Greyserman, Alex, and Kathryn M. Kaminski. 2014. *Trend Following with Managed Futures: The Search for Crisis Alpha*. New York: Wiley Trading.

About the Authors

Kathryn M. Kaminski, Ph.D., CAIA® is the Chief Research Strategist at AlphaSimplex Group. As Chief Research Strategist, Dr. Kaminski conducts applied research, leads strategic research initiatives, focuses on portfolio construction and risk management, and engages in product development. She also serves as a co-portfolio manager for the AlphaSimplex Managed Futures Strategy. Dr. Kaminski's research and industry commentary have been published in a wide range of industry publications as well as academic journals. She is the co-author of the book *Trend Following with Managed Futures: The Search for Crisis Alpha* (2014). Dr. Kaminski holds a B.S. in Electrical Engineering and Ph.D. in Operations Research from MIT.

Ying Yang, M.F.E., is a Junior Research Scientist at AlphaSimplex Group. As a Junior Research Scientist, Ms. Yang focuses on applied research and supports the portfolio management teams. Ms. Yang earned both a B.S. in Mathematics and Physics and a B.A. in Economics and Management from Tsinghua University as well as an M.F.E. from the Haas School of Business at the University of California at Berkeley.

Contact Information

For more information, please contact:
clientservices@alphasimplex.com
617-475-7100

Disclosures

Past performance is not necessarily indicative of future results. Managed Futures strategies can be considered alternative investment strategies. Alternative investments involve unique risks that may be different from those associated with traditional investments, including illiquidity and the potential for amplified losses or gains. Investors should fully understand the risks associated with any investment prior to investing. Commodity-related investments, including derivatives, may be affected by a number of factors including commodity prices, world events, import controls, and economic conditions and therefore may involve substantial risk of loss.

The illustrations and examples presented in this document were created by AlphaSimplex based on unaudited external data and internal methodologies. Accordingly, while the underlying data were obtained from sources believed to be reliable, AlphaSimplex provides no assurances as to the accuracy or completeness of these illustrations and examples. The views and opinions expressed are as of 9/30/2020 and may change based on market and other conditions. There can be no assurance that developments will transpire as forecasted, and actual results may vary. All investments are subject to risk, including risk of loss.

This document has been prepared for informational purposes only and should not be construed as investment advice. AlphaSimplex is not registered or authorized in all jurisdictions and the strategy described may not be available to all investors in a jurisdiction. Any provision of investment services by AlphaSimplex would only be possible if it was in compliance with all applicable laws and regulations, including, but not limited to, obtaining any required registrations. This material should not be considered a solicitation to buy or an offer to sell any product or service to any person in any jurisdiction where such activity would be unlawful.