Risk Variation in Trend-Following Systems

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Introduction

Trend-following strategies are designed to measure the overall strength of trends in a wide range of global markets. They opportunistically follow price trends, building exposures as trends strengthen and reducing exposures as they weaken. As a result, a pure trend-following strategy is often known for having time-varying risk exposures both by asset class and by overall level of risk exposure. In practice, there are several methodologies for readjusting risk in trend-following systems that can impact how risk exposure varies both across assets and by overall level. This paper reviews how risk exposures are determined in trend-following systems to provide some clarity into these options. The paper then turns to 2019, a year where fixed-income trends were a clear outlier, as an example to demonstrate how different risk management decisions can have different results.

What drives risk variation in trend-following systems?

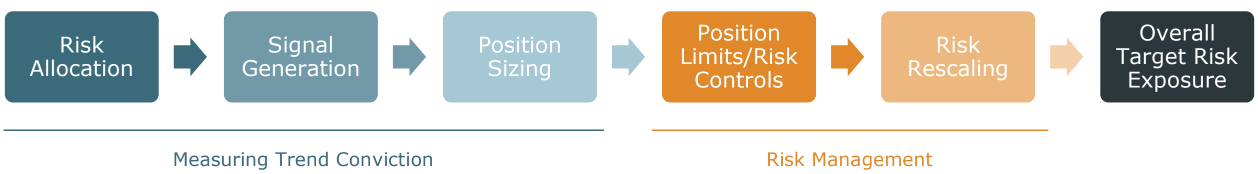

Figure 1: Example of a trend-following system with two stages: (1) measuring and incorporating trend conviction and (2) risk management. The result of these two stages is an overall target risk exposure for the portfolio.

The result of these five key decisions is an overall target risk exposure for the portfolio. For clarity, we review the stages in this process to explain how different design choices might impact risk exposures.

Measuring and Incorporating Conviction

Trend-following systems start with an initial **risk allocation**. Initial risk allocations are similar to loose risk budgets for individual markets. They may also be partitioned to sum to a certain risk budget per asset class. For example, they may be set to have equal risk by asset class including correlations. For a given market, the **trend signal** is then measured for the overall trend strength. This can be done by individual model or across a group of trend-following models. The aggregate signal dictates the amount of the risk budget taken up by that particular market.

If the signal is a one, the entire typical risk budget is used. If the signal is greater than one or less than minus one, more risk than the budget is taken in that market. If the signal is close to zero, there is no measurable trend signal (either long or short), and the amount of risk taken is close to zero.

SIGNAL	AMOUNT OF RISK BUDGET USED
1	100%
<-1 or >1	More than 100%
0 (or close to 0)	Close to 0%

Given the risk allocation and the signal strength for a given market, each **market position** is scaled based on the overall risk per market. For a market with higher volatility (such as Brent crude oil), this will translate to smaller notional dollar positions. For a market with lower volatility (such as short rate contracts), this will translate to larger notional dollar positions.

Risk Management

The remaining steps in building a trend-following system are risk management decisions, including position limits and risk rescaling approaches. Once the positions are determined, a trend-following system generally includes some level of position controls or limits. **Position limits** include gross or net notional limits by market or by asset class, risk limits based on VaR, margin-to-equity limits, and other specific limits. These limits have the effect of trimming desired positions to adhere to these limits.

The second type of key risk management approach in trend following is **risk rescaling**, or a resizing of risk based on different aspects of the portfolio. Risk rescaling decisions come in two primary forms: portfolio level or cross-sectional (across markets). Common portfolio level rescaling options are *constant risk targeting (CRT)* vs. *signal-based risk targeting (SRT)*. CRT requires measuring the overall level of risk in the portfolio and rescaling it to a constant level of risk, such as a 10% annualized volatility target. SRT maintains the overall level of portfolio risk by allowing the risk to scale with aggregate trend signal strength. As a demonstration, Figure 2 plots a schematic of risk exposures using a CRT versus an SRT approach from 2015 to 2019.

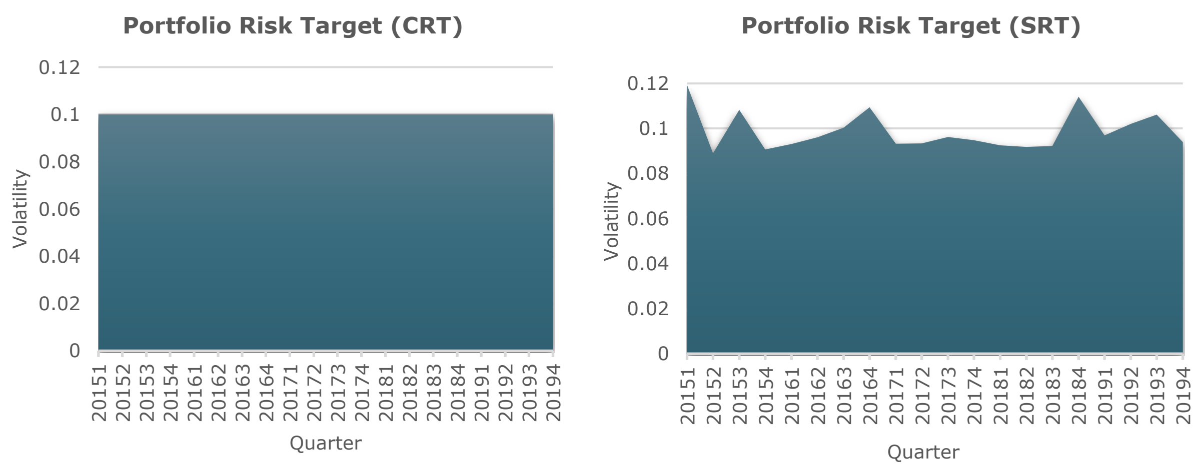

Figure 2: Example of risk exposures using constant risk targeting (CRT) (left) versus signal-based risk targeting (SRT) (right).

Cross-sectional risk rescaling can be done to achieve *equal asset class risk exposures (EAR)*. If risk is not rescaled across the portfolio, it can be denoted as *time-varying risk exposure (TVR)*. Figure 3 plots an example of risk exposures from an EAR approach versus a TVR approach from 2015 to 2019.

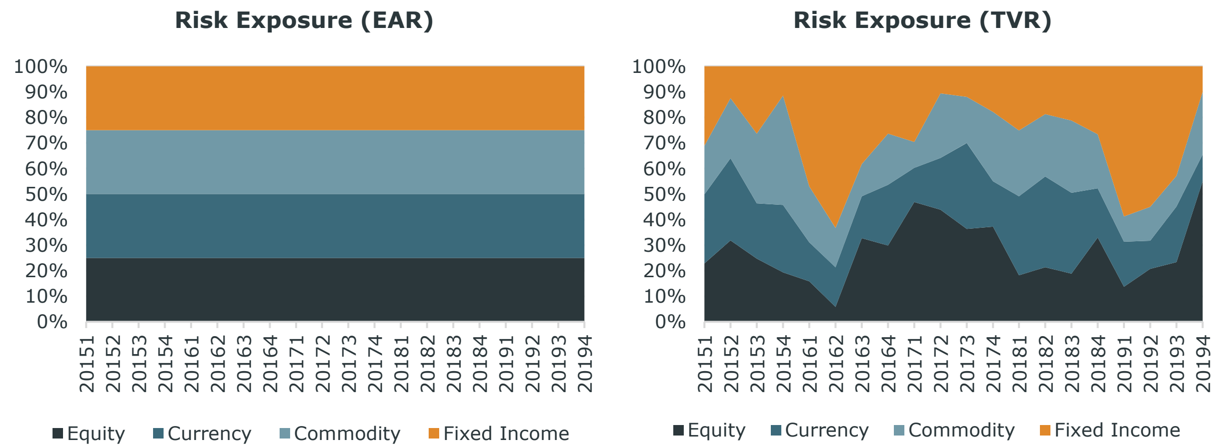

Figure 3: Example of risk exposures from an equal asset class risk approach (left) versus a time-varying risk exposure approach (right) from 2015 to 2019.

Note that a system can be designed to combine any of these two choices. For example, a system could have constant risk exposure which is rescaled to have equal risk to each asset class or a system could have time-varying risk exposure and time-varying overall portfolio risk. The classic pure trend strategy would be time-varying both at the portfolio level and across asset classes. A more detailed analysis of these approaches is described in further detail in the appendix.

		Portfolio-Level Risk	
		Constant Risk Targeting (CRT)	Signal-Based Risk Targeting (SRT)
Cross-Sectional Risk	Equal Asset Class Risk Exposures (EAR)	EAR + CRT	EAR + SRT
	Time-varying Risk Exposure (TVR)	TVR + CRT	TVR + SRT

To help demonstrate how these approaches can yield different results, the following section reviews 2019 as a case study for the different risk rescaling approaches.

A Case Study for Time-varying Risk: 2019

In an earlier piece, we noted that 2019 was a year where global markets were in motion, creating momentous moves and corresponding opportunities for trend-following strategies. However, 2019 was also a year where momentum was clear in bonds but not in other asset classes. To set the stage, we first review what we saw in 2019.

- **Global equities**: Coming out of a difficult year-end in 2018, trend-following strategies were poised to protect in case equities continued to fall further. This all changed on the third trading day of 2019 and markets surged back to finish a banner year (especially in the S&P 500). Navigating these moves was difficult, but after starting off behind trend strategies generally recovered from their first-quarter losses.
- **Currencies**: The strong dollar theme continued from 2018 into 2019, but this theme was constantly tussled around by changes in risk sentiment. These changes led to risk-on moves in emerging markets, particularly against the U.S. dollar, and were driven by currency devaluation events (such as the one in Argentina); the ongoing saga of Brexit; and the banter of trade wars. This constant back and forth made navigating trends in currencies somewhat challenging.
- **Commodities**: Similar to currencies, the ongoing trade discussions created reverting price trends in commodities. These trends were often disrupted by changes in sentiment and varying outlooks for anticipated demand. The commodity sector was also exposed to idiosyncratic risks due to weather or events like the drone attack on the Saudi oil supply in September.
- **Fixed Income**: This leaves us with fixed income. Fixed income was a trend follower's ideal asset class in 2019 as global yields took a steady ride down to historical lows for many global economies. This move was remarkable, and has become one of the top trends within fixed income in the last 20 years.

Given the clear difference across asset classes in terms of trend performance, 2019 is an ideal year to examine how risk exposures can differ across trend-following systems and potentially drive differences in manager performance. In the following sections, we review how risk rescaling would have impacted trend-following performance in 2019.

Signal Generation

Given the strength of trends in fixed income in 2019, it is not surprising that measured trend strength in fixed income was markedly higher. Figure 4 plots the measured relative trend strength by asset class in 2019. Note that fixed income exhibited the largest trends through most of 2019, with trends tapering off by late summer.

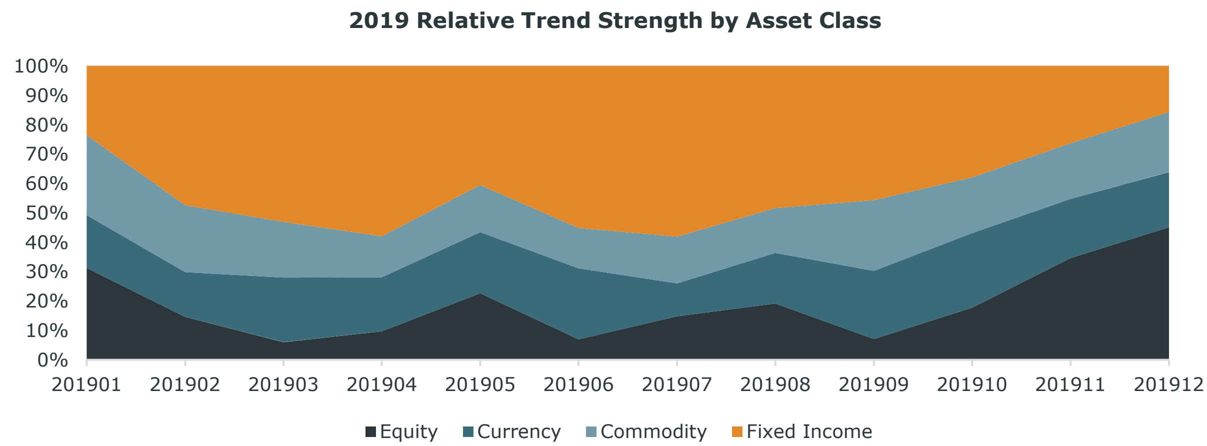

Figure 4: Relative trend strength by asset class in 2019. For demonstrative purposes the total sum of trend signals is aggregated and each asset class is measured relative to the total aggregate trend strength.

Risk exposure by asset class

For simplicity, we consider the difference between the TVR approach, where risk exposures vary over time across asset classes based on the strength of market trends, and the EAR approach, where positions are rescaled to a set risk target for each asset class. For demonstrative purposes, Figure 5 plots the risk allocation by asset class for both TVR and EAR. Note that time-varying risk exposure is consistent with the signal conviction as seen in Figure 4.

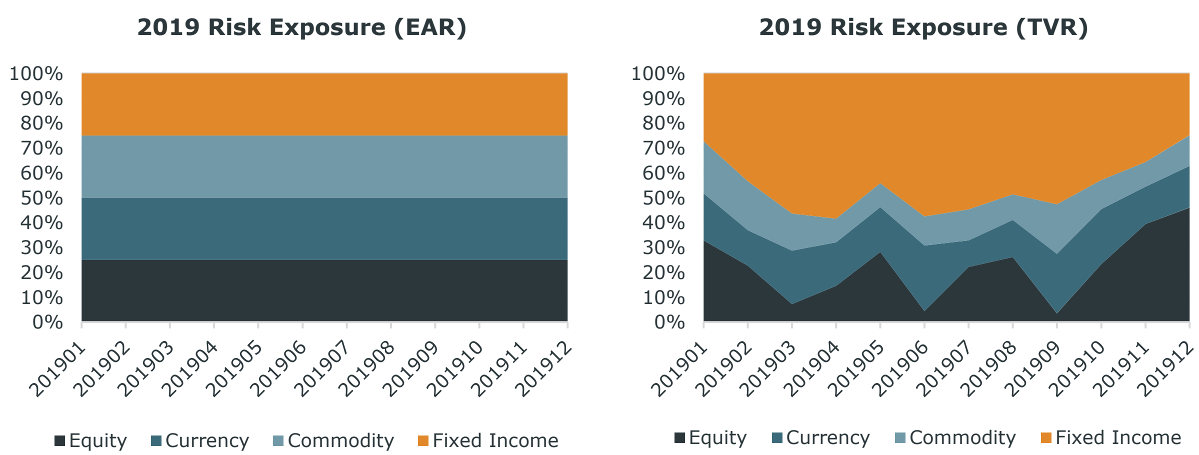

Figure 5: Example of risk exposures from an equal asset class risk (EAR) approach (left) versus a time-varying risk exposure (TVR) approach (right).

In a year like 2019, equal asset class risk exposure would reallocate risk to other asset classes outside of fixed income, negatively impacting overall performance. Figure 6 plots the returns of a representative trend-following system with equal asset class risk exposure or time-varying risk exposure. In this case, constant risk targeting is used to maintain the same overall portfolio risk level. This figure shows how a constant risk level across asset classes would reallocate risk from fixed income, which has higher conviction, into less-trending assets such as currencies or commodities. From Figure 6, it is clear that the TVR approach captures a larger portion of the big trend in global fixed income, particularly in March, May, and August 2019. In a year where other asset classes had weaker trends, the equal risk allocation approach suffered more from reversals in commodities in May and September (although it benefited from these reversals in August).

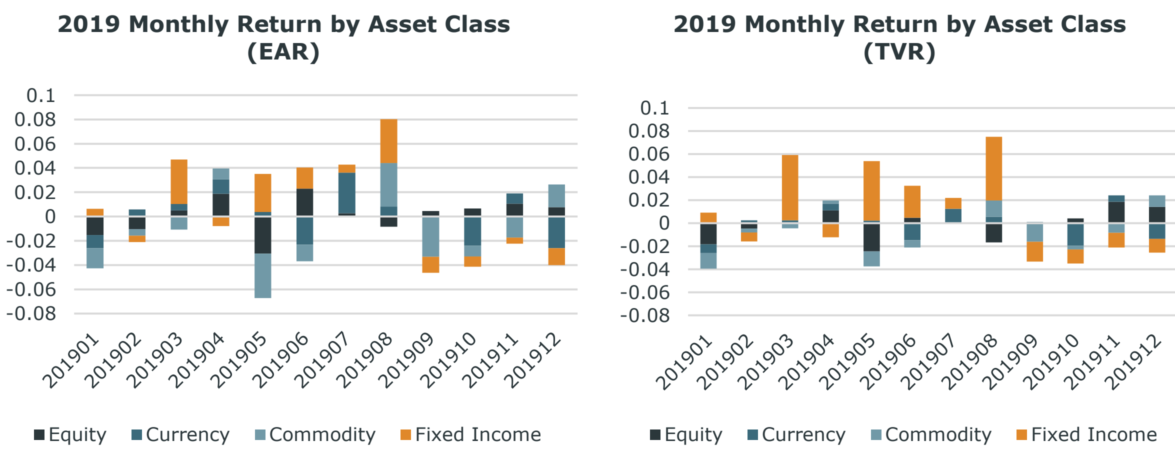

Figure 6: Monthly returns by asset class for a trend-following system with equal asset class risk exposures (EAR) (left) and time-varying risk exposure (TVR) (right). For comparison, constant risk targeting is used in this example.

To compare the performance of EAR and TVR, Figure 7 plots the different approaches in 2019, as well as a variant of the TVR with a constraint of 40% risk exposure per asset class. Consistent with Figure 6, this demonstrates that the ability to vary risk in order to capture the bond trend in 2019 was positive. The constrained TVR approach shows that varying portfolio risk was positive for bonds in 2019, even with risk or position constraints, as these constraints had only a moderate impact on overall performance.

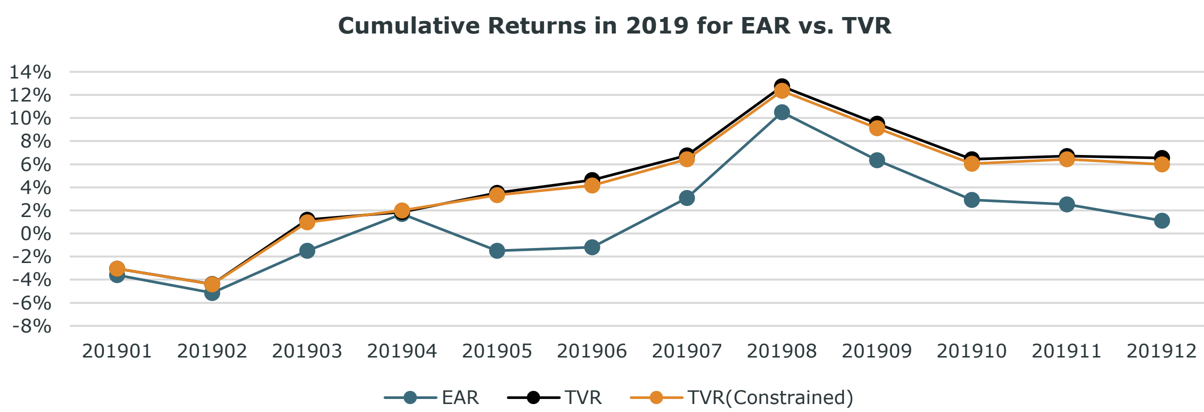

Figure 7: Cumulative performance for equal asset class risk exposure (EAR) and time-varying risk exposure (TVR) both with and without an asset class risk constraint of 40%. All approaches apply constant risk targeting (CRT) for comparison.

Figure 8 plots the performance of these approaches for 2019 by asset class. A 40% cap in risk exposure in fixed income creates a slight reduction in performance.

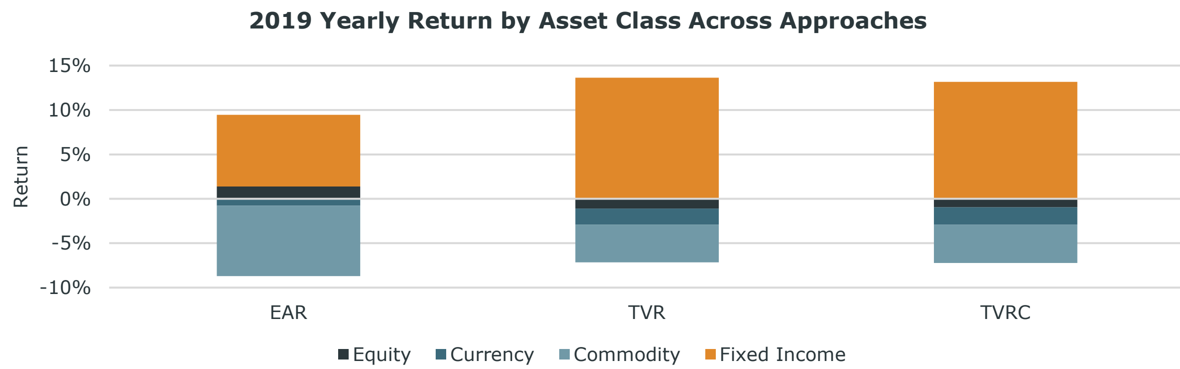

Figure 8: Trend-following performance by asset class for equal asset class risk exposure (EAR) and time-varying risk exposure (TVR) with and without an asset class risk constraint of 40%. All approaches apply constant risk targeting (CRT) for comparison.

Portfolio level risk targeting

In the previous section, we discussed the overall impact of cross-sectional rescaling of risk by asset class for a trend-following system. These decisions impact the overall effect of trends across asset classes in a portfolio. The second area where risk variation can be adjusted is in the overall portfolio-level risk exposure. The classic approach in trend-following is time-varying the level of portfolio risk based on overall signal conviction, or signal-based risk targeting (SRT). Its counterpart is constant risk targeting (CRT). Figure 9 plots the impact of signal risk targeting in 2019. From this graph we can see that overall aggregate signals varied in 2019, with the highest signal strength in January and late summer 2019.

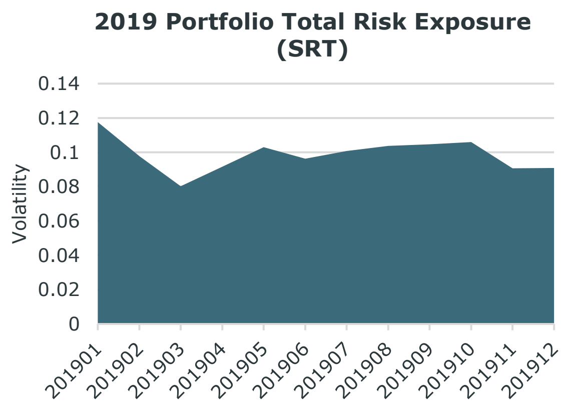

Figure 9: An example of signal risk targeting (SRT) in 2019.

To compare the effect of varying the overall level of risk, Figure 10 plots the impact of signal risk targeting in 2019 versus constant risk targeting. The signal risk targeting approach takes more risk in January when trends reverted in many asset classes and takes less risk during March 2019 when there were sizable trends in bond markets. This example demonstrates that varying risk based on total signal strength can create variations in both risk exposure and returns.

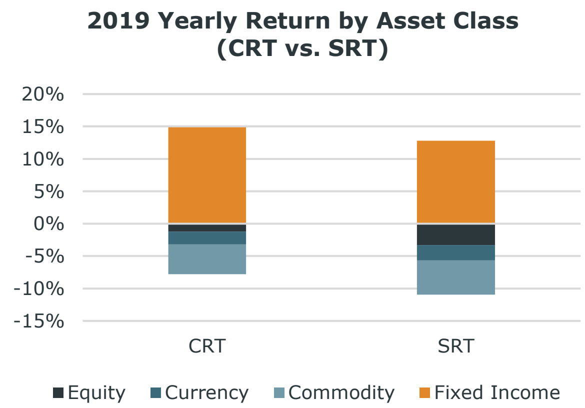

Figure 10: An example of the performance of a representative trend-following system by asset class in 2019 based on constant risk targeting (CRT) and signal-based risk targeting (SRT). For comparison, neither representative system rescales risk by asset class following a TVR approach.

Putting all of the approaches together provides a sample performance of all four combinations, both cross-sectional and based on risk level. Figure 11 plots the cumulative return for each of these approaches in 2019. Note that the time-varying allocation across asset classes performed the best in a year where one asset class was a clear outperformer. It is important to note that this example is not meant to suggest that one technique is preferred over others. However, it is important to understand how these decisions can impact overall performance dispersion.

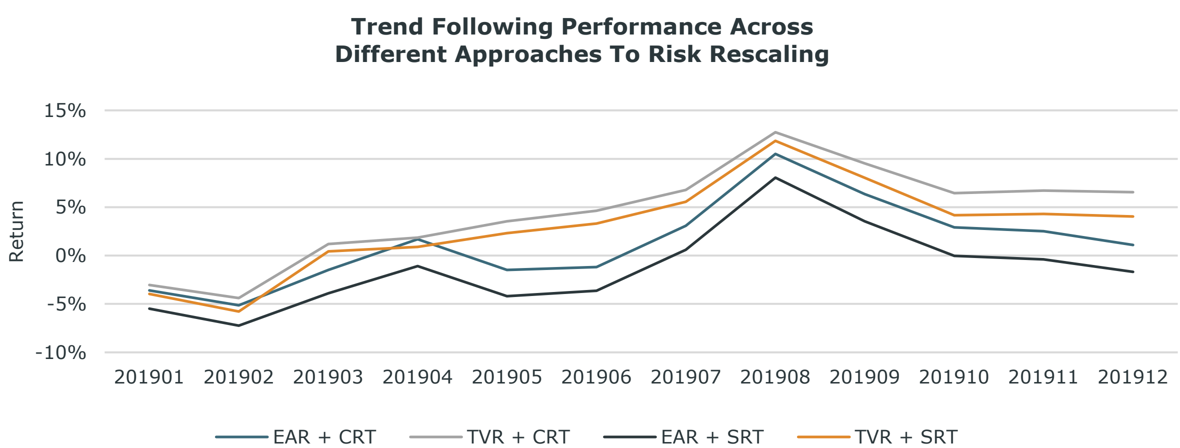

Figure 11: Performance of a representative trend-following system with different risk rescaling approaches, both cross-sectional (TVR vs. EAR) and overall portfolio level (CRT vs. SRT) in 2019.

Summary

This paper reviews the design decisions in trend-following systems by dividing the process into two stages: (1) measuring conviction and (2) risk management. This paper focuses in on the different choices for rescaling risk at the portfolio level and across asset classes to demonstrate how these decisions can impact the overall portfolio. Given that 2019 was a year where trends were somewhat concentrated in fixed-income markets, the paper uses 2019 as an example to demonstrate how final risk exposures based on risk management decisions can create somewhat different performance.

Appendix: Some Simple Math for Demonstrative Purposes

Using terminology similar to Greyserman and Kaminski (2014), for a given market i let θ be the risk allocation, c be the capital allocated to each market, σ be the measured risk in the traded contracts, and s be the signal conviction. The desired position size for a given market is:

$$w = \frac{v}{P \cdot PV \cdot c} = s\frac{\theta}{\sigma}$$

In the cross section, the overall risk per asset class can be calculated and each position per asset class can be rescaled to set the risk per asset class to be equal. If this re-scaling does not occur the risks are allowed to vary across time as signal strength varies. For an asset class I where a market i is contained in I (for example, the S&P 500 Futures contract is contained in the set of equity markets), the new weight in market i is defined by:

$$\widetilde{w}_i = w_i \times \frac{\sigma_I}{\sqrt{{w_I}'\Sigma_I w_I}} \quad i \in I$$

Here, $\sum_I$ represents the correlation matrix across markets in each asset class I and σ_I represents the target for each asset class (for example 0.25 times the overall portfolio target). If this portfolio is also constant risk targeted (represented by σ_T) the final portfolio weights for a market i in asset class I would be

$$\widehat{w}_i = \widetilde{w}_i \times \frac{\sigma_T}{\sqrt{\widetilde{w}'\Sigma\widetilde{w}}}$$

Here, $\sum$ represents the covariance matrix for the entire portfolio. Note if the total risk exposure is less than the target the portfolio scales up positions. If the risk is greater than the target risk exposures are scaled down.

Signal-based risk targeting would not adjust the position sizes and leave the size of the positions to scale linearly with the signal strength ($\sum_{i \in stk,bnd,fx,comdty} |s_i|$). To avoid excess risk, position limit constraints would trim certain positions and keep the risk within bounds (8% – 12%). In contrast, constant risk targeting would take all the positions in the portfolio, calculate the overall risk allocated, and then rescale all positions by a constant level term to maintain a constant measured risk. It is important to note that constant risk targeting incorporates the correlations across different positions in the portfolio.

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