Breaking Bad Trends

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We document and quantify the negative impact of trend breaks (i.e., turning points in the trajectory of asset prices) on the performance of standard trend-following strategies across several assets and asset classes. The frequency of trend breaks has increased in recent years, which can help explain the lower performance of monthly trend following in the last decade. We illustrate how to repair trend-following strategies by exploiting the return forecasting properties of the different types of trend breaks: market corrections and rebounds. We construct dynamic multi-asset trend-following portfolios, which harvest more than double the average returns of standard trend-following investing strategies over the last decade.

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Trend-following investing (i.e., time-series momentum strategies) can successfully exploit trends in asset prices as demonstrated in numerous research studies over the last 30 years.[1] Such a strategy varies its position in an individual asset over time based on the sign of trailing returns over some fixed lookback window (e.g., monthly trading as a function of the most recent 12 months of returns). Going long during sustained periods of uptrend—bull markets—or short during sustained periods of downtrend—bear markets—tends to be a good bet under such a strategy.

Trend will occasionally break down, however, and reverse direction (i.e., at market corrections and rebounds). At and after these breaks, or turning points, in momentum, such trend following tends to place bad bets because trailing returns can reflect an older, inactive trend direction. Faster trend signals (e.g., only a few months of trailing returns), rather than solving the problem, increase the tendency of placing bad bets because faster signals often reflect noise instead of a true turn in trend. The momentum literature, however, has dedicated relatively little attention to this Achilles' heel of trend investing.[2]

We study the impact of trend breaks and present three main new findings. First, we document and quantify the impact of turning points on trend following. We define a turning point for an asset as a month in which its slow (longer lookback horizon) and fast (shorter lookback horizon) momentum signals differ in their indications to buy or sell. We find a negative relationship between the number of turning points that an asset experiences and the risk-adjusted performance of its 12-month trend-following strategy.[3] This relationship mani-

[1]The literature documents that asset returns measured over the recent past are positively correlated with future returns (Jegadeesh and Titman, 1993, 2001, Asness, 1994, Conrad and Kaul, 1998, Lee and Swaminathan, 2000, and Gutierrez and Kelley, 2008). This phenomenon is stable across assets and countries (Rouwenhorst, 1998, Griffin et al., 2003, Israel and Moskowitz, 2012, and Asness et al., 2013). Studies of the merits of trend following and time-series momentum investing, in particular, include the following: Cutler et al. (1991), Silber (1994), Fung and Hsieh (1997, 2001), Erb and Harvey (2006), Moskowitz et al. (2012), Menkhoff et al. (2012), Baltas and Kosowski (2013), Hurst et al. (2013), Baltas and Kosowski (2015), Levine and Pedersen (2016), Georgopoulou and Wang (2017), Hurst et al. (2017), Ehsani and Linnainmaa (2019), Garg et al. (2019), Gupta and Kelly (2019), and Babu et al. (2020a,b).

[2]The *cross-sectional* momentum literature has explored themes related to market cycles and breaking points (Cooper et al., 2004, Daniel and Moskowitz, 2016, and Daniel et al., 2019). Cooper, Gutierrez, and Hameed use a slow trailing three-year return to define two market states—"up" and "down"—whereas we use the intersection of slow and fast trailing return signals to define four market phases and to characterize trend breaking points. Daniel and Moskowitz (2016) study cross-sectional momentum crashes and recoveries and propose a dynamic cross-sectional weighting strategy. Daniel et al. (2019) use a two-state hidden Markov model of unobserved "turbulent" and "calm" states to predict tail risk in cross-sectional momentum portfolios. We apply the dynamic time-series momentum approach of Garg et al. (2019), who blend slow and fast strategies using four-state cycle-conditional information, and apply the approach to country equity indices. We adapt this approach to study the sensitivity of several asset markets and multi-asset trend-following portfolios to breaking points.

[3]A 12-month lookback window is the standard window length for time-series momentum analyzed in the literature (Moskowitz et al., 2012, and Huang et al., 2019), among others. Some studies consider shorter lookback windows such as 1, 2, or 3 months, or consider averages of strategies with 12-month and shorter

fests not only across a diverse collection of assets from different asset classes, but also carries over to multi-asset portfolios of trend-following strategies. Although such a relationship might not seem surprising to at least some extent, its economic impact can be substantial. For a multi-asset trend-following portfolio normalized to have 10% annualized volatility over the last 30 years, a one-standard-deviation increase in the average number of breaking points per year (+0.45) is associated with a decrease of approximately 9.2 percentage points in its annual portfolio return. Moreover, we show that turning points reflect distinct information not transmitted by return volatility. Not only are turning points and return volatility uncorrelated, but volatility exhibits no significant relationship with risk-adjusted trend-following performance.

Second, we find that the number of breaking points can help explain the deterioration of trend-following performance in more recent years. Trend-following individual assets with monthly trading has performed well across several asset classes over several decades. This performance, however, has deteriorated in the most recent decade.[4] During this recent period, the average number of turning points experienced across assets has increased: 6 of the most recent 10 years are in the top one-third over the last 30 years when ranked by highest-to-lowest average number of turning points. An increase in turning points means a decrease in sustained periods of trend (i.e., bull or bear markets), the market phases in which trend following is most effective. Babu et al. (2020a) show that "market moves," measured as the absolute value of asset annual Sharpe ratios, are contemporaneously positively related to the performance of trend-following strategies and that the decrease in market moves in recent years can help explain the deterioration of trend-following performance. Because this relationship is contemporaneous rather than predictive, it is not clear that we can use this relationship to improve trend-following strategies. In contrast, turning points (observed difference between shorter and longer lookback horizons) can be predictive of subsequent returns and used to improve trend-following strategies (Garg et al., 2019).

As our third main finding, we present trend-following strategies that react *dynamically* to asset turning points and that improve performance of multi-asset trend-following portfolios, especially in months after asset turning points, which have become more frequent in recent years. Our analysis leverages and extends our work on momentum turning points (Garg

lookback windows (e.g., Babu et al., 2020a). We look at such alternatives in a later section.

[4] Performance of the Société Générale (SG) Trend Index, an equally-weighted index of major trend-focused funds, incepted at the beginning of 2000, experienced an annualized Sharpe ratio of approximately 0.41 over its first decade (2000-2009). In its second decade (2010-2019), its annualized Sharpe ratio fell by nearly half (0.21) and the index experienced its worst drawdown, losing more than 20% over the 45-month period 2015-04 to 2019-01. Likewise, the annualized Sharpe ratio of a hypothetical multi-asset portfolio of 12-month trend-following strategies with monthly rebalancing fell by over half in the recent decade compared to its level over the last 30 years. (See static multi-asset trend-following performance in later sections.)

et al., 2019), in which we show that the intersection of slow and fast time-series momentum signals can provide *predictive* information about returns on equity indices. This information, in turn, can be used to improve time-series momentum strategies. Our approach is not to be confused with moving average crossovers. Levine and Pedersen (2016) show that moving average crossovers are essentially equivalent to *static* blends of time-series momentum strategies. Moreover, Hurst et al. (2013) show that the returns of trend-following strategies such as Managed Futures funds and CTAs can be explained by *static* blends of time-series momentum strategies.

At a high level, our approach follows two basic steps. First, we partition an asset's return history into four observable phases—Bull, Correction, Bear, and Rebound—by relying on the agreement or disagreement of slow and fast trailing momentum signals. Second, we examine the information content of these states for *subsequent* return behavior and use this to specify an implementable "dynamic" trend-following strategy that adjusts the weight it assigns to slow and fast time-series momentum signals after observing market breaks (Corrections or Rebounds). Our application of this dynamic approach to multi-asset trend-following portfolios illustrates that not only can we help explain weaker performance in recent years, but we can construct a trend-following strategy that can exploit this relationship and recover much of the losses experienced by static-window trend following in the last decade.

Data and Turning Points

Data

We use monthly returns for 55 futures, forwards, and swaps markets across four major asset classes: 12 equity indices, 10 bond markets, 24 commodities, and 9 currency pairs. Our sample begins in 1971-01 for some assets and we add each asset when its return data become available through 2019-12. Our time series of returns is based on holding the front-month contract (or 1-month forward or 10-year swap) and swapping to a new front contract as its expiration date approaches. See Appendix A for more details.

Time-Series Momentum

For each of the 55 markets, we construct a binary time-series momentum strategy following the methodology described by Garg et al. (2019). Our "static" 12-month trend strategy uses a fixed lookback window size of 12 months of prior returns and goes long one unit if the asset's trailing 12-month return is positive; otherwise, it goes short one unit.[5] This simple design is similar to that used by Goyal and Jegadeesh (2017) and Huang et al. (2019). Note that we do not scale the momentum signal by trailing volatility as do Moskowitz et al. (2012) and we do not exponentially weight past prices.[6] We call these simple time-series momentum strategies "static" to contrast with our "dynamic" strategies, which we discuss later.

Turning Points

We define asset market turning points based on the methodology described in Garg et al. (2019). For each of the 55 markets, we construct two binary time-series momentum signals, labeled SLOW and FAST, based on longer and shorter lookback windows of prior returns, respectively. For each asset i, its slow and fast momentum signals for month m are the averages of its monthly excess returns in preceding months:

$$x_m^{i,\mathrm{SLOW}} = \frac{1}{k_{\mathrm{SLOW}}^i} \sum_{m'=m-1}^{m-k_{\mathrm{SLOW}}^i} r_{m'}^i, \tag{1}$$

$$x_m^{i,\mathrm{FAST}} = \frac{1}{k_{\mathrm{FAST}}^i} \sum_{m'=m-1}^{m-k_{\mathrm{FAST}}^i} r_{m'}^i, \tag{2}$$

where k_{SLOW}^i and k_{FAST}^i are the number of lookback months, respectively, with $k_{\mathrm{SLOW}}^i > k_{\mathrm{FAST}}^i$ and $r_{m'}^i$ is the excess return on asset i in month m' (prior to month m). For example, SLOW may be the average of the prior 12 months of returns ($k_{\mathrm{SLOW}}^i = 12$), while FAST may be the average of the prior 2 months of returns ($k_{\mathrm{FAST}}^i = 2$). Typically, SLOW would be based on 12 months or more, while FAST would be 3 months or fewer to capture the difference between longer- and shorter-term trends.

We say that asset i is at a *turning point* in month m if the signs of its slow and fast signals disagree. The basic idea is that if the average return over a shorter period is pointing in a different direction than the average return over a longer period (say, up versus down), then the market may have encountered a break in trend (say, from downtrend to uptrend).[7] If a trend break has indeed occurred, then slower signals prescribe bad bets (e.g., shorting

[5] We define the asset's trailing 12-month return as the arithmetic average of the preceding 12 months of monthly returns in excess of cash, which is the implied market borrowing rate for institutions.

[6] Volatility scaling may have a distinct effect from time-series momentum (e.g., Kim et al., 2016, Moreira and Muir, 2017, and Garg et al., 2019) and we seek to not intermix the two mechanisms.

[7] Given our definition, observing a turning point does not necessarily reflect an actual trend break. In particular, in noisy periods, some turning points can be false alarms of a true turn. In later sections, we will refine our definition of turning points to distinguish between turning points from up to down (Corrections) and from down to up (Rebounds). For now, our classification is sufficient to illustrate our key finding.

the market based on an older downward trend when the market is recently trending up). On the other hand, if disagreements reflect noise in fast signals rather than true trend breaks, then faster signals prescribe bad bets.

Note that a turning-point month for an asset is observable at the beginning of the month because it is based only on trailing returns. Later we will exploit this property to construct time-series momentum strategies with improved performance. For now, we focus on the within-year relationship between annual turning points and trend returns.

We define the number of turning points per asset per year as

$$\mathrm{TP}_y^i := \text{number of months } m \text{ in year } y \text{ such that } \mathrm{sign}(x_m^{i,\mathrm{SLOW}}) \neq \mathrm{sign}(x_m^{i,\mathrm{FAST}}). \quad (3)$$

For each asset, TP_y^i is an integer between 0 and 12, which counts the number of months within year y that were turning-point months for asset i.

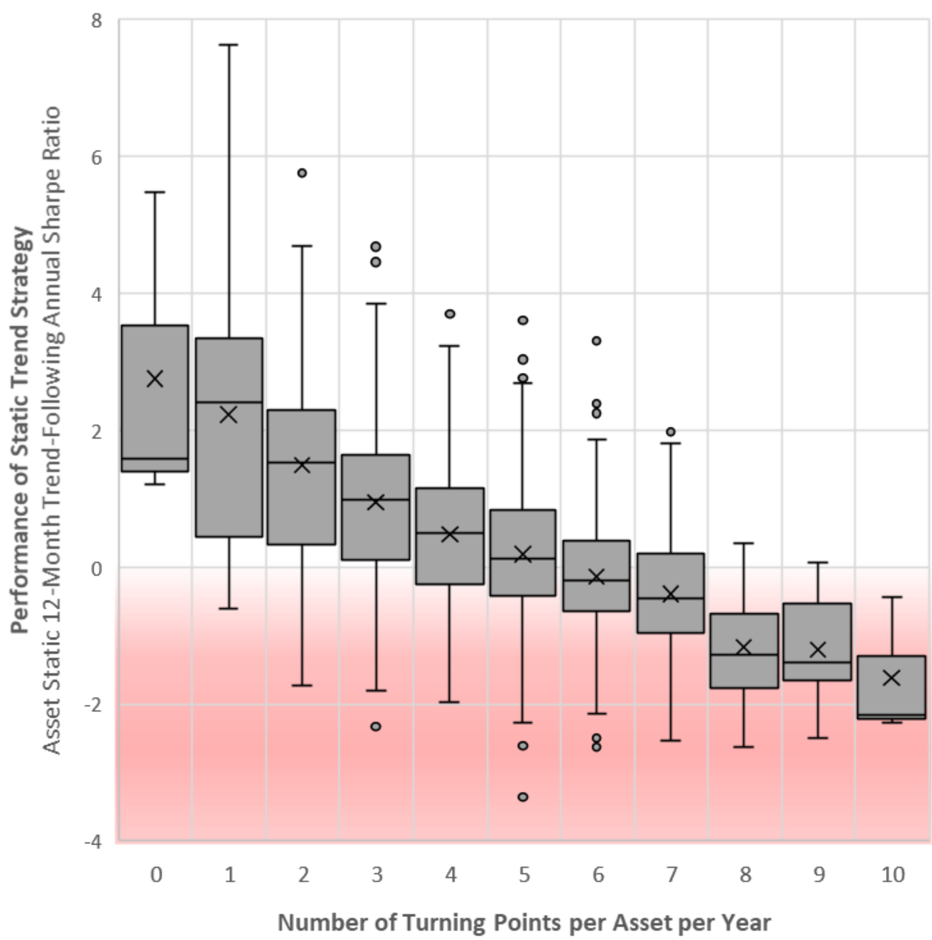
Turning Points and Static Trend

In Exhibit 1, we plot the distribution of annual Sharpe ratios of static 12-month trend-following strategies against the number of asset turning points in the year for all assets each calendar year over the last 30 years. For each asset in each calendar year, we calculate the number of turning points as the frequency of months within the year for which the signs of its trailing 12-month and 1-month returns differ (i.e., $k_{\mathrm{SLOW}}^i = 12$ and $k_{\mathrm{FAST}}^i = 1$ for all i). Static 12-month trend goes long one unit if the asset's trailing 12-month return is positive; otherwise, it goes short one unit. We calculate an asset's trend-following Sharpe ratio each year as the annual excess return of trend following divided by the annualized realized monthly volatility of trend following.[8] There are 1,561 asset-year observations in total. Each box plot gives a vertical representation of the distribution of observations that have the given number of turning points. The horizontal lines of each box indicate the quartiles of the distribution with the mean indicated by $\times$. The height of the box represents the interquartile range (IQR). The whiskers extend up and down from the box to the most extreme data points that are within 1.5 times the IQR above or below the box. We consider values beyond the whiskers as outliers, represented by dots.

Exhibit 1 shows a negative relation between the frequency of turning points and trend-following performance across assets. As the number of turning points per year increases, the distribution of risk-scaled performance of trend following during the year shifts downward.[9]

[8] Performance is gross of any transaction costs or costs of rolling contracts.
[9] In our sample, none of the assets has 11 or 12 turning points in any year.

Exhibit 1: Static Trend Performance vs. Number of Turning Points per Asset per Year (1990-01 to 2019-12)



Notes: For each asset in each calendar year, we calculate the number of turning points as the frequency of months within the year for which the signs of its trailing 12-month and 1-month returns differ. Static 12-month trend goes long one unit if the asset's trailing 12-month return is positive; otherwise, it goes short one unit. We calculate an asset's trend-following Sharpe ratio each year as the annual excess return of trend following the asset divided by the annualized realized monthly volatility of trend following the asset. There are 1,561 asset-year observations in total, none of which has 11 or 12 turning points in any year. The horizontal lines of each box plot indicate the 25th percentile, median, and 75th percentile, respectively. The height of the box reflects the interquartile range (IQR). The mean is indicated by ×. The whiskers extend up from the top of the box to the largest data point that is less than or equal to 1.5 times the IQR and down from the bottom of the box to the smallest data point that is larger than 1.5 times the IQR. We consider values outside this range as outliers, represented by dots.

The exhibit also shows how costly turning points can be for trend following. For assets with 6 or more turning points within a year, typical (median) returns to static trend following are negative. For assets with 8 or more turning points within a year, the vast majority of returns to static trend following are negative with annualized Sharpe ratios below −1.0 on average across assets.

The frequency of turning points is not a proxy for return volatility. First, our measure of trend-following performance is on a risk-adjusted basis. We measure the trend-following performance of each asset in Exhibit 1 by its Sharpe ratio, which scales its annual returns by its annualized volatility. This adjustment puts different assets on a comparable risk basis. Second, the negative relationship evident in Exhibit 1 vanishes if we replace the number of turning points by bins of asset volatilities (see Exhibit B.1 in Appendix B). Third, the number of turning points per asset per year is approximately uncorrelated with return volatility: 0.02 correlation. High or low volatility can appear during periods of sustained uptrend or downtrend (bull or bear markets) as well as at and after turning points.

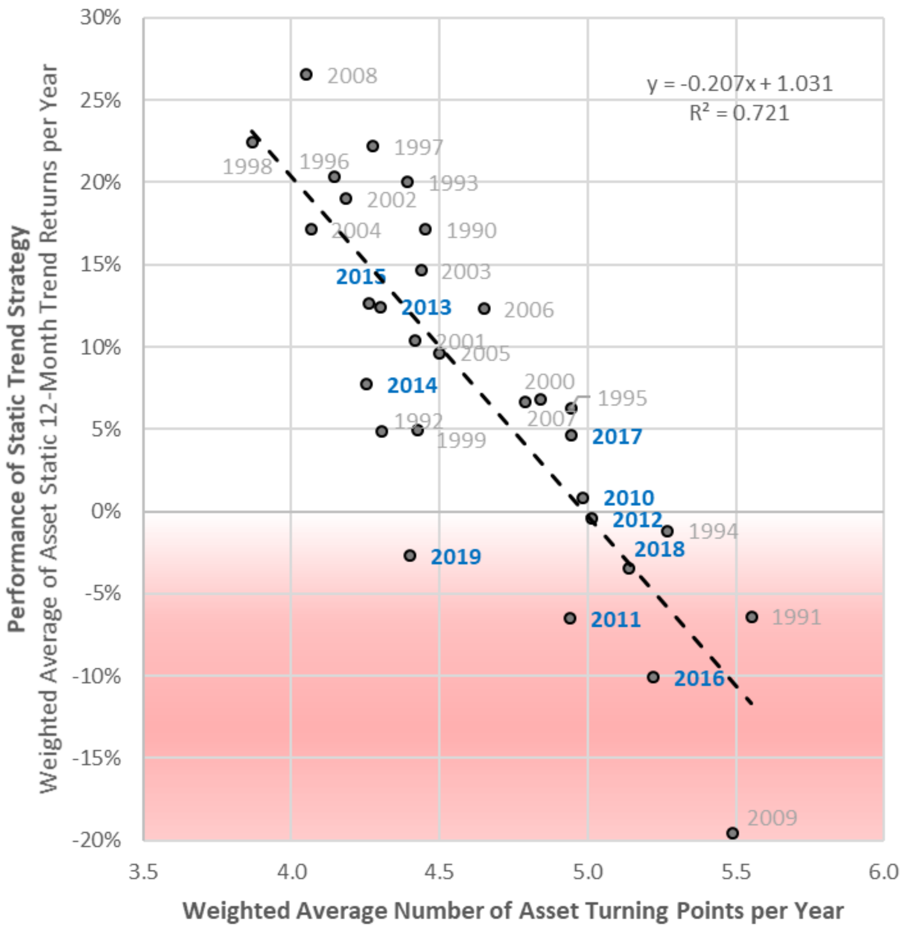
The negative relationship between turning-point frequency and trend-following performance across the distributions of individual assets carries over to multi-asset trend-following portfolios. In Exhibit 2, we plot the annual returns of a multi-asset portfolio of static 12-month trend-following strategies as a function of the average number of turning points for those assets in the year. Each year y, we compute the weighted average number of turning points across all assets, TP_y, by allocating equal weight to each asset's value within its asset class and equal weight to each asset class across the four asset classes. For example, we assign 1/96 weight to each of the 24 commodities (1/24 to each commodity and 1/4 to commodities overall). Similarly, we construct a multi-asset static trend portfolio return as the equally weighted average of individual asset static trend-following returns.[10]

Similar to Exhibit 1, Exhibit 2 shows a distinct negative relationship between the number of turning points and the risk-adjusted performance of trend-following strategies. The downward sloping fitted trend line ($R^2 = 0.72$ and slope -0.21) quantifies the negative relationship. A one-standard-deviation increase in the weighted average number of asset turning points (+0.45, say, from 4.50 to 4.95) translates to approximately 9.2 percentage points lower annual return, which is economically significant relative to the 10% annualized volatility level over the sample.

Exhibit 3 shows the distribution of the number of turning points per year per asset across all 55 assets over the last 30 years split into the first 20 years and the last 10 years. The last 10 years exhibit an upward shift in the number of turning points relative to the first 20 years. This phenomenon is also present in Exhibit 2. Six of the most recent 10 years (highlighted

[10] Equally-weighted averages reflect more volatility from riskier assets such as commodities and equities. Our results are similar throughout our analyses if we weight each asset by its full-sample inverse volatility or by its trailing inception-to-date inverse volatility in order to normalize each asset's underlying risk contribution to the multi-asset portfolio.

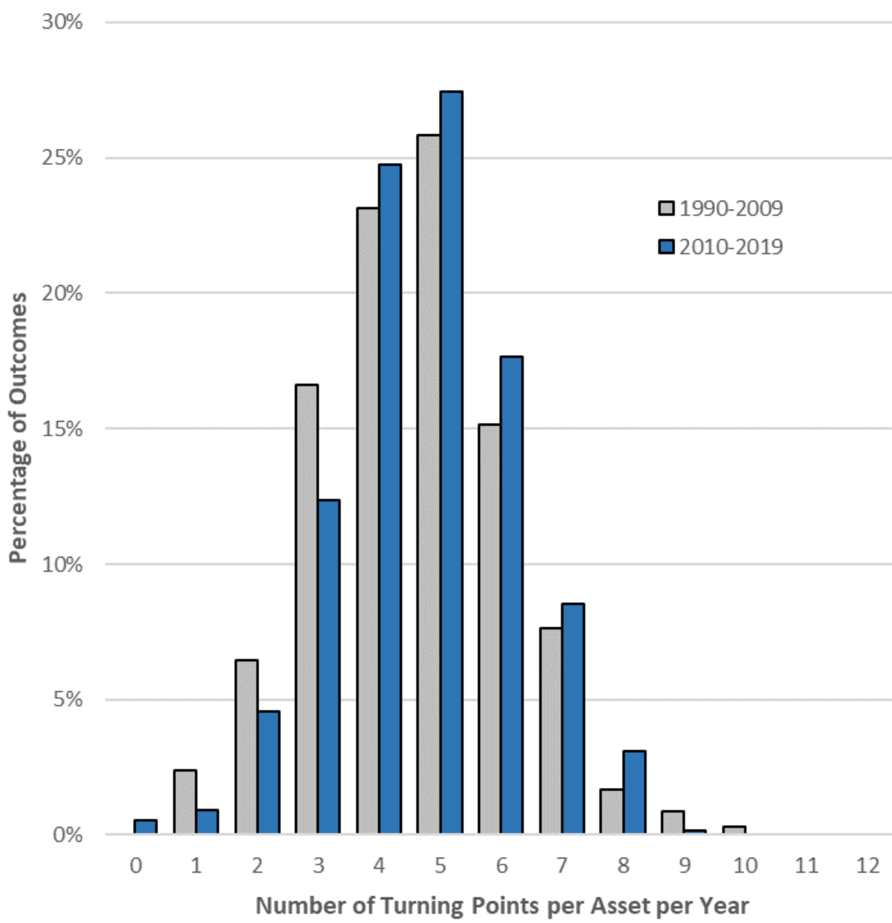
Exhibit 2: Multi-Asset Static Trend Portfolio Performance vs. Weighted Average Number of Asset Turning Points per Year (1990-01 to 2019-12)



Notes: For each asset in each calendar year, we calculate the number of turning points as the frequency of months within the year for which the signs of its trailing 12-month and 1-month returns differ. Static 12-month trend goes long one unit if the trailing 12-month return is positive; otherwise it goes short one unit. We equally weight each asset within its asset class and equally weight across the four asset classes in both the weighted average of asset turning points per year and in the multi-asset trend portfolio excess return. We normalize portfolio returns to have 10% annualized monthly volatility over the sample. We highlight with bold text the points corresponding to the most recent 10 years.

with boldface text) have a weighted average number of turning points that rank in the top 10 years of the 30-year period. Given the negative relationship between the number of turning points and trend-following performance highlighted in Exhibits 1 and 2, this shift can help explain the deterioration of trend-following performance in the recent decade.

Exhibit 3: Asset Turning Points Have Been More Frequent in Recent Years: Empirical Distribution of Number of Asset Turning Points per Year (1990-01 to 2019-12)



Notes: For each asset in each calendar year, we calculate the number of turning points as the frequency of months within the year for which the signs of its trailing 12-month and 1-month returns differ. 12-month trend goes long one unit if the trailing 12-month return is positive; otherwise it goes short one unit. We express the total number of assets in each category in each time range (1990-2009 or 2010-2019) as a percentage of all category outcomes in that time range. There are 1,011 observations from 1990 to 2009 and 550 observations from 2010 to 2019.

Turning Points and Dynamic Trend

In this section, we adapt the dynamic trend-following methodology of Garg et al. (2019) to each asset in our universe of 55 assets. Based on the signs of the slow and fast momentum signals in equations (1) and (2), we define four market states for each asset in each month as follows:

$$s_m^i = \begin{cases} \text{Bull}, & \text{if } x_m^{i,\text{SLOW}} \geq 0 \text{ and } x_m^{i,\text{FAST}} \geq 0, \\ \text{Correction}, & \text{if } x_m^{i,\text{SLOW}} \geq 0 \text{ and } x_m^{i,\text{FAST}} < 0, \\ \text{Bear}, & \text{if } x_m^{i,\text{SLOW}} < 0 \text{ and } x_m^{i,\text{FAST}} < 0, \\ \text{Rebound}, & \text{if } x_m^{i,\text{SLOW}} < 0 \text{ and } x_m^{i,\text{FAST}} \geq 0. \end{cases} \tag{4}$$

Note that the union of Correction and Rebound phases equals turning-point phases of our earlier definition: $\text{sign}(x_m^{i,\text{SLOW}}) \neq \text{sign}(x_m^{i,\text{FAST}})$ if and only if $s_m^i = \text{Correction or Rebound}$.[11] We also define the returns to the slow and fast momentum strategies for each asset in each month as follows:

$$r_m^{i,\text{SLOW}} = \begin{cases} r_m^i, & \text{if } x_m^{i,\text{SLOW}} \geq 0, \\ -r_m^i, & \text{if } x_m^{i,\text{SLOW}} < 0, \end{cases} \tag{5}$$

$$r_m^{i,\text{FAST}} = \begin{cases} r_m^i, & \text{if } x_m^{i,\text{FAST}} \geq 0, \\ -r_m^i, & \text{if } x_m^{i,\text{FAST}} < 0. \end{cases} \tag{6}$$

Recall from (1) and (2) that each signal x_m is determined with information from months *prior* to month m so that the state s_m is observable at the beginning of the month and applied to a position until the next month to deliver each r_m.

The dynamic trend strategy return for each asset in each month blends the fast and slow returns in a way that can vary after observing different market states as follows:

$$r_m^{i,\text{DYN}} = \begin{cases} r_m^i, & \text{if } s_m^i = \text{Bull}, \\ -r_m^i, & \text{if } s_m^i = \text{Bear}, \\ (1 - a_{\text{Co}}^i) r_m^{i,\text{SLOW}} + a_{\text{Co}}^i r_m^{i,\text{FAST}}, & \text{if } s_m^i = \text{Correction}, \\ (1 - a_{\text{Re}}^i) r_m^{i,\text{SLOW}} + a_{\text{Re}}^i r_m^{i,\text{FAST}}, & \text{if } s_m^i = \text{Rebound}. \end{cases} \tag{7}$$

Each mixing parameter (a_{Co}^i or a_{Re}^i) is a mixing weight placed on the fast strategy—after observing either a Correction or Rebound, respectively. Behavior after Bull and Bear states

[11] As with our definition of a turning point, noisy periods can create temporary and unintuitive correction or rebound classifications, which could be refined by other definitions beyond the scope of this study.

mimics the static strategy. For our historical simulation, we estimate these mixing parameters from historical returns in months following Corrections and Rebounds prior to portfolio formation. Mixing parameters are estimated ex ante and do not use data from the future. For each asset without sufficient history prior to the beginning of the evaluation period in 1990-01, our sample is reduced by up to 48 months of return history needed to warm up the mixing parameter estimates. Implementation details are given in Appendix C.

The mixing parameters tilt each asset's strategy away from or toward its fast trend strategy in an intuitive way. Intuitively, if historical returns tend to be positive after Corrections (when the slow strategy goes long and the fast strategy goes short), then $a^i_{\mathrm{Co}} < \frac{1}{2}$, reflecting a tilt *away from* FAST. In contrast, if historical returns tend to be positive after Rebounds (when the slow strategy goes short and the fast strategy goes long), then $a^i_{\mathrm{Re}} > \frac{1}{2}$, reflecting a tilt *toward* FAST. If historical returns are negative after such states, then the direction of the tilt reverses. If the estimate is noisy, then there is shrinkage to the no-information position of $\frac{1}{2}$.

This strategy is implementable as a trading strategy in real time, not just in a backtest. We form the multi-asset dynamic trend portfolio as follows. Using the equations described above for each asset, at the beginning of each month we blend the asset's slow and fast trend strategies according to the observed market phase, which depends only on returns from prior months. We form the multi-asset dynamic trend portfolio return as a weighted-average of individual asset dynamic trend returns. Similar to our static portfolio, dynamic portfolio asset weights are equally weighted within each asset class, and asset class weights are equal across the four asset classes.

Our framework supports dynamic blending of two time-series momentum strategies having slow and fast momentum signals. We illustrate the potential of dynamic trend strategies to handle turning points with a simple example, which uses a common choice of slow and fast horizons across all assets. The related work by Babu et al. (2020a) studies the connection between market moves (absolute value of asset annual Sharpe ratios) and the performance of trend-following strategies formed as the average of 1-, 3-, and 12-month static time-series momentum strategies on each asset. We use the 2- and 12-month lookback horizons for fast and slow signals, respectively, in our empirical analysis. The faster 2-month signal approximates the information in the short lookback windows of 1- and 3- months, and we blend this 2-month strategy dynamically with the slower 12-month signal-based strategy.[12]

[12]The fast signal we use here differs from the 1-month signal that Garg et al. (2019) use to study individual equity index applications. We highlight that each asset may respond differently to the market phases defined by different choices of slow and fast momentum strategies. For example, the disagreement between 3-month and 12-month trend directions might yield better informative states for currencies while the disagreement between 1-month and 12-month trend directions might be more informative for equities. Likewise, the

In Exhibit 4, we compare the annualized monthly returns of this multi-asset dynamic trend portfolio alongside the 12-month static multi-asset trend portfolio, with each portfolio normalized to have 10% volatility over the stated sample periods.

Exhibit 4 also shows the decomposition of these returns into returns following Bulls or Bears and returns following turning points, Corrections or Rebounds. Multi-asset static trend generates approximately 7.5% annualized average return over the 30-year evaluation period, yet only 1.8% in the most recent decade. Moreover, the vast majority of the returns to the multi-asset static trend portfolio in either evaluation period can be attributed to months after Bull or Bear phases.

In contrast, the multi-asset dynamic trend portfolio not only generates returns after Bull or Bear phases in similar magnitude to the static strategy, but also generates returns in months after turning points. Average returns of both static and dynamic methods have decreased in recent years; however, dynamic trend generates a 4.3% average return in the recent decade, which is more than double the 1.8% generated by static trend. Moreover, the bulk of those gains are from returns harvested after turning points.

We compare the performance of our dynamic trend strategy with the performance of various static trend strategies and with blends of static trend strategies in Exhibit 5. We draw similar inferences from these alternative static specifications. Faster static trend strategies or static blends of static trend strategies struggle to generate returns after turning points, particularly in the most recent decade.

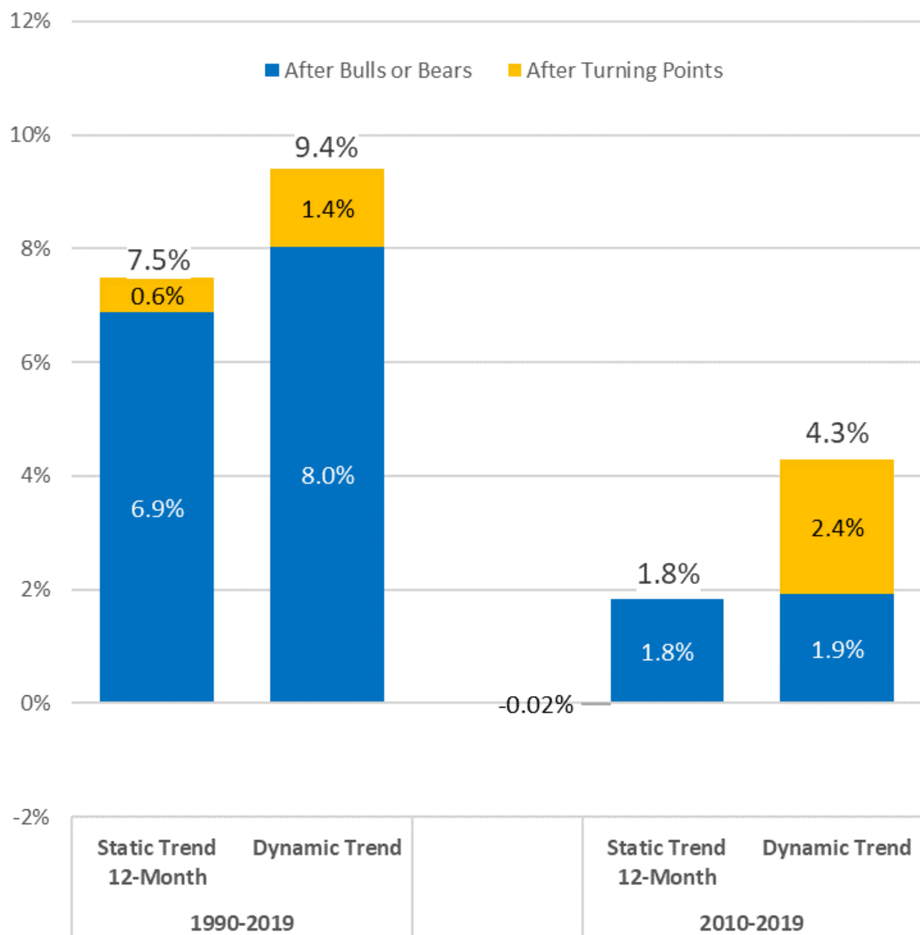
Conclusion

Trend-following strategies at the monthly trading frequency have experienced notably weaker performance over the most recent decade compared with the prior two decades. The frequency of turning points in the trajectory of asset price trends—as measured by disagreements between slow and fast trailing momentum signals—can help explain this phenomenon. Recent years have exhibited more turning points across assets and asset classes and, therefore, fewer periods of sustained uptrend or downtrend (i.e., bull and bear markets) across all assets, those phases in which trend following is most effective.

We show that observed market corrections and rebounds carry predictive information about subsequent returns and we utilize such breaks to enhance the performance of trend-following strategies. We illustrate this fact with a multi-asset *dynamic* trend portfolio that focuses on addressing performance after turning points, while following a simple static trend strategy after bull and bear markets of each asset. We demonstrate that dynamic trend

diversification properties across different assets may also vary with the choice of slow and fast signals.

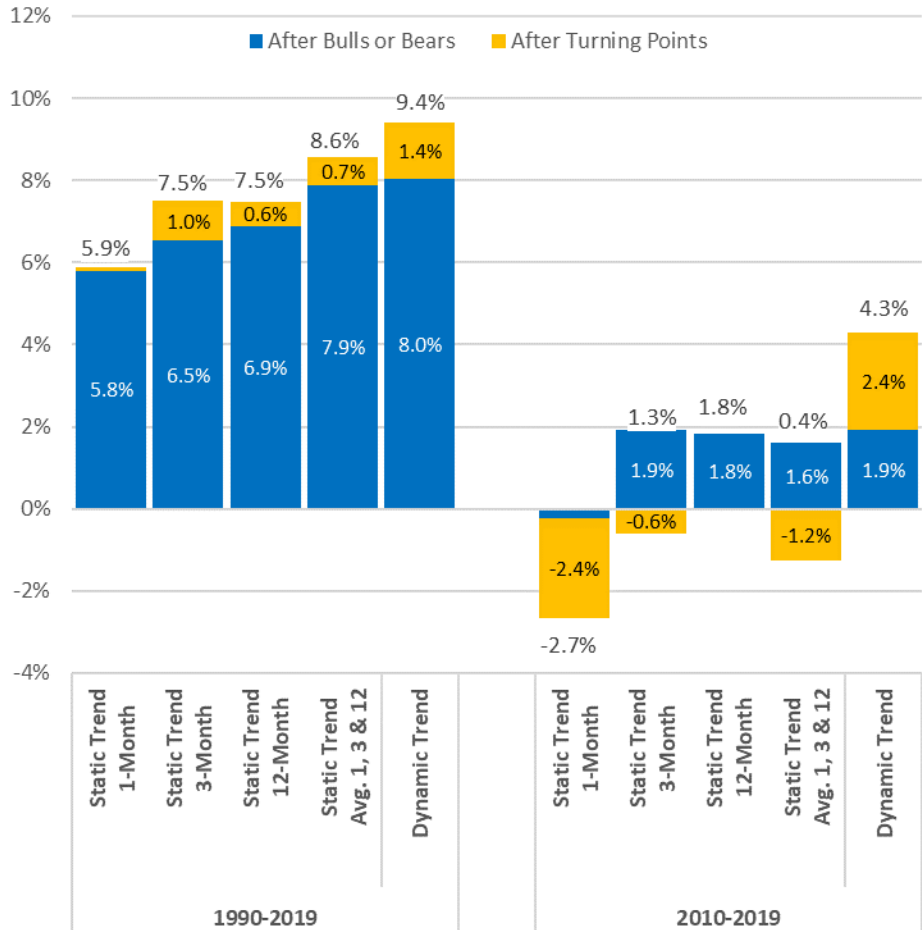
Exhibit 4: Average Annualized Return Decomposition for Multi-Asset Trend-Following Portfolios using Static (12-Month) or Dynamic Trend Strategies for Each Asset: Last 30 Years and Most Recent Decade (1990-01 to 2019-12 and 2010-01 to 2019-12)



Notes: For each asset in each month, static trend goes long one unit if the trailing 12-month return is positive; otherwise, it goes short one unit. For each asset in each month, we label the asset's market state as of the beginning of the month as one of Bull, Correction, Bear, or Rebound as follows. Bull = its trailing 12- and 2-month returns are positive (non-negative); Correction = its trailing 12-return is positive (non-negative), but its trailing 2-month return is negative; Bear = its trailing 12- and 2-month returns are negative; and Rebound = its trailing 12-month return is negative, but its trailing 2-month return is positive. Turning points are defined as months in a Correction or Rebound state. For each asset, dynamic trend blends the 12- and 2-month static strategies using the mixing parameter on the 2-month strategy of a^i_{Co} after Corrections and a^i_{Re} after Rebounds. Implementation details are summarized in Appendix C. Reported averages are of returns scaled to achieve 10% annualized monthly volatility for the total return over the stated period.

following can harvest returns after turning points, returns that might have been lost under standard trend following.

Exhibit 5: Average Annualized Return Decomposition for Multi-Asset Trend-Following Portfolios using Static Trend or Dynamic Trend Strategies for Each Asset: Last 30 Years and Most Recent Decade (1990-01 to 2019-12 and 2010-01 to 2019-12)



Notes: For each asset in each month, static trend goes long one unit if the trailing k-month return is positive; otherwise goes short one unit; where $k = 1, 3, 12$. "Avg. 1, 3 & 12" is the average of each static strategy. For each asset in each month, we label the asset's market state as of the beginning of the month as one of Bull, Correction, Bear, or Rebound as follows. Bull = its trailing 12- and 2-month returns are positive (non-negative); Correction = its trailing 12-return is positive (non-negative), but its trailing 2-month return is negative; Bear = its trailing 12- and 2-month returns are negative; and Rebound = its trailing 12-month return is negative, but its trailing 2-month return is positive. Turning points are defined as months in a Correction or Rebound state. For each asset, dynamic trend blends the 12- and 2-month static strategies using the mixing parameter on the 2-month strategy of a^i_{Co} after Corrections and a^i_{Re} after Rebounds. Implementation details are summarized in Appendix C. Reported averages are of returns scaled to achieve 10% annualized monthly volatility for the total return over the stated period.

Appendix A. Data Details

We use monthly returns from 55 futures, forwards, and swaps markets starting from the dates listed below through 2019-12. Roll schedule is based on liquidity of contracts. Our universe consists of contracts that are front (and among most liquid contracts) and are rolled out to next nearest (and liquid) contract at the beginning of the expiration month of the contract.

Equity Futures

Our equities universe includes 12 developed country indices: Australia (ASX SPI 200 Index, 1980-02), Canada (S&P/TSX 60 Index, 1980-02), France (CAC40 10 Index, 1980-02), Germany (DAX Index, 1980-02), Hong Kong (Hang Seng Index, 1991-07), Italy (FTSE/MIB Index, 1980-02), Japan (Nikkei 225 Index, 1980-02), Netherlands (AEX Index, 1980-02), Spain (IBEX 35 Index, 1987-05), Sweden (OMXS30 Index, 1982-03), United Kingdom (FTSE 100 Index, 1980-02), and United States (S&P 500 Index, 1980-02). Pre-2002 returns data are from Datastream (broad market total return in excess of the country's 3-month government bill rate). Data for 2002 and beyond are from Bloomberg (futures, return of front contract).

Bond Futures and Swaps

Our bond universe includes 10 developed country indices: Australia (Australia 10Y Bond, 1987-12), Canada (Canada 10Y Bond, 1987-12), France (Euro-OAT Bond, 1987-12), Germany (Euro-Bund Long Term, 1987-12), Italy (EURO-BTP Bond, 1991-05), Japan (Japan 10Y Bond, 1987-12), New Zealand (New Zealand 10Y Bond, 2004-01), Switzerland (Switzerland 10Y Bond, 2008-08), United Kingdom (Gilt Long Bond, 1987-12), and United States (US Treasury 10Y Bond, 1987-12). Pre-2002 returns data for all countries except New Zealand and Switzerland are from Datastream (broad market total return in excess of the country's short rate). Data for 2002 and beyond for all countries except New Zealand and Switzerland are from Bloomberg (futures, return of front contract). Data for New Zealand and Switzerland are from Bloomberg (swaps, return of 10Y swap) for each country.

Commodity Futures

Our commodities universe includes 24 commodities across 6 sectors (energy, grains, industrial metals, livestock, precious metals, and softs): Aluminum (1999-01), Brent Crude (1989-08), Cocoa (1971-01), Coffee (1972-11), Copper (1999-01), Corn (1971-01), Cotton (1971-01), Feeder Cattle (1971-12), Gasoil (1986-07), Gasoline (1985-01), Gold (1975-01), Heating Oil (1978-12), Kansas Wheat (1971-01), Lead (1999-01), Lean Hogs (1971-01), Live Cattle (1971-01), Natural Gas (1990-05), Nickel (1999-01), Silver (1971-01), Soybeans (1971-01), Sugar (1971-01), Wheat (1971-01), WTI Crude (1983-04), and Zinc (1999-01). Returns data for all commodities except Aluminum, Copper, Lead, Nickel, and Zinc are from Commodity Research Bureau (futures, return of front contract). Returns data for Aluminum, Copper, Lead, Nickel, and Zinc are from Bloomberg (futures, return of front contract).

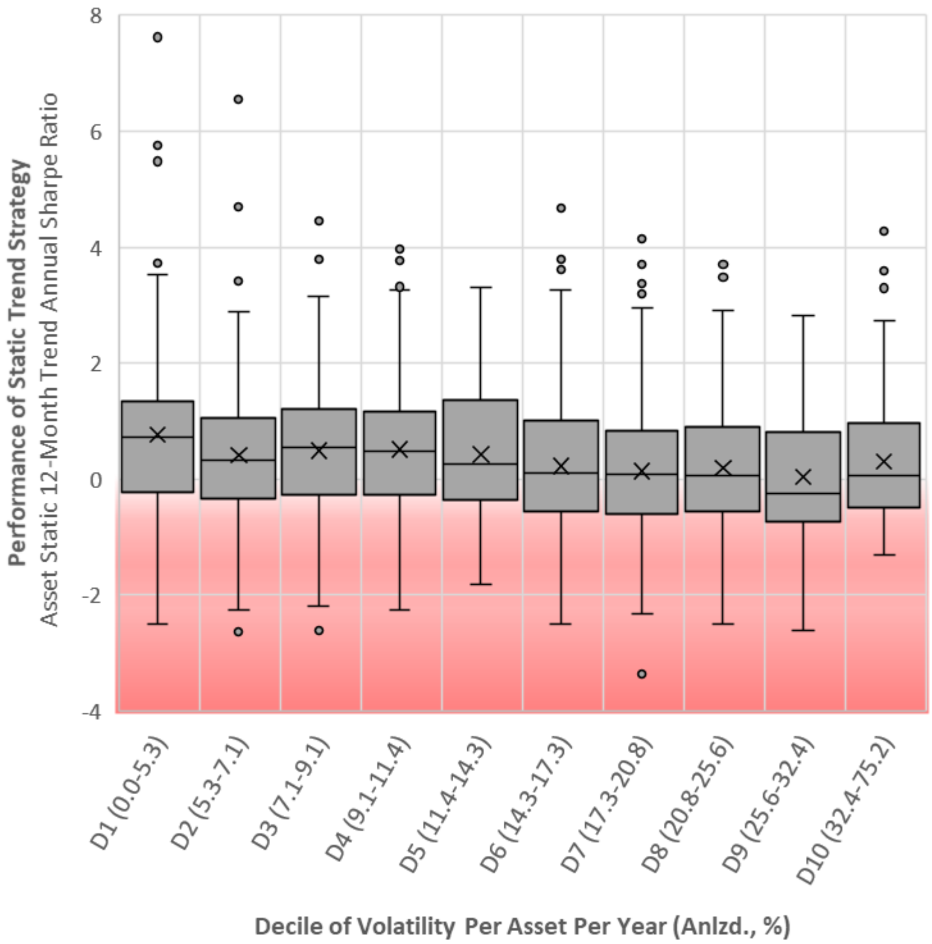
Currency Forwards

Our currency universe includes 9 developed currency pairs against the U.S. dollar: Australia (AUD/USD, 1985-01), Canada (CAD/USD, 1985-01), Eurozone (EUR/USD, 1983-11), Japan (JPY/USD, 1983-11), New Zealand (NZD/USD, 1985-01), Norway (NOK/USD, 1985-01), Sweden (SEK/USD, 1985-01), Switzerland (CHF/USD, 1983-11), and United Kingdom (GBP/USD, 1983-11). Pre-2002 returns data are from Datastream (forwards, ratio of 1-month forward to spot). Data for 2002 and beyond are from Bloomberg (forwards, ratio of 1-month forward to spot).

Appendix B. Static Trend Performance vs. Volatility

Exhibit B.1 shows essentially no relationship between static trend-following performance and volatility.

Exhibit B.1: Static Trend Performance vs. Volatility Decile per Asset per Year (1990-01 to 2019-12)



Notes: For each asset in each calendar year, we calculate its annualized monthly return volatility. We group all asset-year volatilities into ten deciles. Static 12-month trend goes long one unit if the asset's trailing 12-month return is positive; otherwise, it goes short one unit. We calculate an asset's trend-following Sharpe ratio each year as the annual excess return of trend following the asset divided by the annualized realized monthly volatility of trend following the asset. The horizontal lines of each box plot indicate the 25th percentile, median, and 75th percentile, respectively. The height of the box reflects the interquartile range (IQR). The mean is indicated by ×. The whiskers extend up from the top of the box to the largest data point that is less than or equal to 1.5 times the IQR and down from the bottom of the box to the smallest data point that is larger than 1.5 times the IQR. We consider values outside this range as outliers, represented by dots.

Appendix C. Dynamic Trend Mixing Parameters

We estimate dynamic slow and fast mixing parameters based on the theoretical analysis of Garg et al. (2019), who derive the optimal mixing parameter pair to apply after Corrections and Rebounds of an asset in order to maximize the Sharpe ratio of dynamic trend-following the asset. We use the first two letters of each market state name as an abbreviation. Mixing parameters are computed as follows:

$$a^i_{\mathrm{Co}} = \frac{1}{2}\left(1 - \frac{1}{C^i}\frac{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Co}}}{\mathrm{AVG}}\, r^i_{m'}}{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Co}}}{\mathrm{AVG}}\, (r^i_{m'})^2}\right), \tag{C1}$$

$$a^i_{\mathrm{Re}} = \frac{1}{2}\left(1 + \frac{1}{C^i}\frac{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Re}}}{\mathrm{AVG}}\, r^i_{m'}}{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Re}}}{\mathrm{AVG}}\, (r^i_{m'})^2}\right), \tag{C2}$$

$$C^i = \frac{\underset{\substack{m'<m\\ s^i_{m}=\mathrm{Bu}}}{\mathrm{FREQ}}}{\underset{\substack{m'<m\\ s^i_{m}=\mathrm{Bu\ or\ Be}}}{\mathrm{FREQ}}}\frac{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Bu}}}{\mathrm{AVG}}\, r^i_{m'}}{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Bu\ or\ Be}}}{\mathrm{AVG}}\, (r^i_{m'})^2} - \frac{\underset{\substack{m'<m\\ s^i_{m}=\mathrm{Be}}}{\mathrm{FREQ}}}{\underset{\substack{m'<m\\ s^i_{m}=\mathrm{Bu\ or\ Be}}}{\mathrm{FREQ}}}\frac{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Be}}}{\mathrm{AVG}}\, r^i_{m'}}{\underset{\substack{m'<m\\ s^i_{m'}=\mathrm{Bu\ or\ Be}}}{\mathrm{AVG}}\, (r^i_{m'})^2}, \tag{C3}$$

where $\underset{\substack{m'<m\\ s^i_{m'}=s}}{\mathrm{AVG}}$ denotes the arithmetic average of its argument over all months m' prior to month m in which the market state for asset i was s and $\underset{\substack{m'<m\\ s^i_{m}=\mathrm{Be}}}{\mathrm{FREQ}}$ denotes the frequency of months m' prior to month m in which the market state for asset i was s. The scalar C^i in (C3) captures the ratio of expected momentum returns following Bulls or Bears relative to their risk and the relative likelihood of encountering these states in history. We subtract scaled average returns after Bears because we go short after Bears. C^i is typically positive and used as a normalizer in (C1) and (C2).

Each mixing parameter $(a^i_{\mathrm{Co}}, a^i_{\mathrm{Re}})$ is the mixing weight on the fast strategy. In our historical simulations, we update each mixing parameter estimate every 60 months using inception-to-prior-month returns data. If either mixing parameter estimate falls outside the interval $[0, 1]$, we set its value to the nearest endpoint of this interval, 0 or 1. We require at least 12 months of historical returns in each phase for each asset to estimate the mixing parameters; otherwise, the asset is excluded from the multi-asset portfolio for that month. We use data prior to 1990-01, where available, to warm up estimates of dynamic mixing parameters. Returns of an asset enter the dynamic multi-asset trend portfolio whenever such conditions are met.

Note that the mixing parameter equations reflect the following intuition. After Corrections (when the slow strategy goes long and the fast strategy goes short), if returns tend to be positive, then $a^i_{\text{Co}} < \frac{1}{2}$, reflecting a tilt away from FAST in proportion to the volatility of those returns. After Rebounds (when the slow strategy goes short and the fast strategy goes long), if returns tend to be positive, then $a^i_{\text{Re}} > \frac{1}{2}$, reflecting a tilt toward FAST in proportion to the volatility of those returns.

References

Asness, C. S., 1994. Variables that explain stock returns. Ph.D. thesis, University of Chicago.

Asness, C. S., Moskowitz, T. J., Pedersen, L. H., 2013. Value and momentum everywhere. Journal of Finance 68, 929–985.

Babu, A., Hoffman, B., Levine, A., Ooi, Y. H., Schroeder, S., Stamelos, E., 2020a. You can't always trend when you want. Journal of Portfolio Management 46, 1–17.

Babu, A., Levine, A., Ooi, Y. H., Pedersen, L. H., Stamelos, E., 2020b. Trends everywhere. Journal of Investment Management 18.

Baltas, A. N., Kosowski, R., 2013. Momentum strategies in futures markets and trend-following funds. Tech. rep., working Paper, Imperial College Business School, London.

Baltas, A. N., Kosowski, R., 2015. Demystifying time-series momentum strategies: Volatility estimators, trading rules and pairwise correlations. Tech. rep., working Paper, Imperial College Business School, London.

Conrad, J., Kaul, G., 1998. An anatomy of trading strategies. Review of Financial Studies 11, 489–519.

Cooper, M. J., Gutierrez, R. C., Hameed, A., 2004. Market states and momentum. Journal of Finance 59, 1345–1366.

Cutler, D. M., Poterba, J. M., Summers, L. H., 1991. Speculative dynamics. The Review of Economic Studies 58, 529–546.

Daniel, K., Jagannathan, R., Kim, S., 2019. A hidden markov model of momentum. Tech. rep., national Bureau of Economic Research.

Daniel, K., Moskowitz, T. J., 2016. Momentum crashes. Journal of Financial Economics 122, 221–247.

Ehsani, S., Linnainmaa, J., 2019. Factor momentum and the momentum factor, available at SSRN 3014521.

Erb, C. B., Harvey, C. R., 2006. The tactical and strategic value of commodity futures. Financial Analysts Journal 62, 69–97.

Fung, W., Hsieh, D. A., 1997. Empirical characteristics of dynamic trading strategies: The case of hedge funds. Review of Financial Studies 10, 275–302.

Fung, W., Hsieh, D. A., 2001. The risk in hedge fund strategies: Theory and evidence from trend followers. Review of Financial Studies 14, 313–341.

Garg, A., Goulding, C. L., Harvey, C. R., Mazzoleni, M. G., 2019. Momentum turning points, available at SSRN 3489539.

Georgopoulou, A., Wang, J. G., 2017. The trend is your friend: Time-series momentum strategies across equity and commodity markets. Review of Finance 31, 1557–1592.

Goyal, A., Jegadeesh, N., 2017. Cross-sectional and time-series tests of return predictability: What is the difference? Review of Financial Studies 31, 1748–1824.

Griffin, J. M., Ji, S., Martin, J. S., 2003. Momentum investing and business cycle risk: Evidence from pole to pole. Journal of Finance 58, 2515–2547.

Gupta, T., Kelly, B. T., 2019. Factor momentum everywhere. Journal of Portfolio Management 45, 13–36.

Gutierrez, R. C., Kelley, E. K., 2008. The long-lasting momentum in weekly returns. Journal of Finance 63, 415–447.

Huang, D., Li, J., Wang, L., Zhou, G., 2019. Time-series momentum: Is it there? Journal of Financial Economics Forthcoming.

Hurst, B., Ooi, Y. H., Pedersen, L. H., 2013. Demystifying managed futures. Journal of Investment Management 11, 42–58.

Hurst, B., Ooi, Y. H., Pedersen, L. H., 2017. A century of evidence on trend-following investing. Journal of Portfolio Management 44, 15–29.

Israel, R., Moskowitz, J. T., 2012. The role of shorting, firm size, and time on market anomalies. Journal of Financial Economics 108, 275–301.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56, 699–720.

Kim, A. Y., Tse, Y., Wald, J. K., 2016. Time series momentum and volatility scaling. Journal of Financial Markets 30, 103–124.

Lee, C., Swaminathan, B., 2000. Price momentum and trading volume. Journal of Finance 55, 2017–2069.

Levine, A., Pedersen, L. H., 2016. Which trend is your friend? Financial Analyst Journal 72, 51–66.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Currency momentum strategies. Journal of Financial Economics 106, 620–684.

Moreira, A., Muir, T., 2017. Volatility-managed portfolios. Journal of Finance 72, 1611–1644.

Moskowitz, T. J., Ooi, Y. H., Pedersen, L. H., 2012. Time series momentum. Journal of Financial Economics 104, 228–250.

Rouwenhorst, K. G., 1998. International momentum strategies. Journal of Finance 53, 267–284.

Silber, W. L., 1994. Technical trading: When it works and when it doesn't. Journal of Derivatives 1, 39–44.