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Research

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 monthly trend-following strategies across several assets and asset classes. In the years of the US economy's expansion following the global financial crisis of 2008, we find an increase in the frequency of trend breaks, which helps explain the lower performance of these trend strategies during this period. We illustrate how to repair such strategies using a dynamic trend-following approach that exploits the return-forecasting properties of the two types of trend breaks: market corrections and rebounds.

Keywords: Asset pricing; behavioral finance; market timing; mean reversion; momentum speed; time-series momentum; trend following; turning points; volatility timing

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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 three decades.[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—has been a historically profitable strategy in many asset classes.

A trend must eventually break down, however, and reverse direction. At and after these breaks, or turning points in momentum, trend following can place bad bets because trailing returns 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.[2] The momentum literature, however, has dedicated relatively little attention to this Achilles' heel of trend investing.[3]

We study the impact of trend breaks and present three main findings. First, we document and quantify the impact of turning-point frequency on the profitability of trend following. Following Goulding, Harvey, and Mazzoleni (2023), 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.[4] This relationship not only manifests across a diverse collection of assets from different asset classes but also carries over to multi-asset portfolios of trend-following strategies.[5] Although such a relationship might not seem surprising to at least some extent, its economic impact can be

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substantial. For a multi-asset trend-following portfolio normalized to 10% annualized volatility over the 33-year period 1990–2022, a one–standard deviation increase in the average number of breaking points per year (+0.47) is associated with a decrease of about 8.9 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-point frequency and return volatility virtually 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 the expansion period (2009–2019) following the global financial crisis (GFC) of 2008.[6] During this 11-year expansion period, the average number of turning points experienced across assets increased: nine of these years are at or above the median number of turning points in our 33-year sample period.[7] 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 values of an asset's 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. Turning-point frequency and market moves have an intuitive positive relationship: Having more turning points in the trajectory of an asset's prices entails fewer opportunities for consecutive monthly returns of the same sign to accumulate to larger magnitude returns for the year (whether positive or negative) for trend following to take advantage of. Therefore, the negative association of turning-point frequency with the performance of trend-following strategies is consistent with the positive association between market moves and the performance of trend-following strategies. However, because the relationship of market moves to trend-following performance is contemporaneous rather than predictive, whether market moves can be applied to develop more-profitable trend-following strategies is unclear. In contrast, turning points (observed differences between shorter and longer lookback horizons) can be predictive of subsequent returns and used to improve the profitability of trend-following strategies (Goulding, Harvey, and Mazzoleni 2023).

As our third main finding, we present trend-following strategies that react *dynamically* to asset turning points. We follow the approach of Goulding, Harvey, and Mazzoleni (2023), who dynamically blend slow and fast momentum strategies based on four-state cycle-conditional information to study trend following for equity indices.[8] We extend this approach to multiple assets and asset classes to show that the intersection of slow and fast time-series momentum signals can provide *predictive* information that improves the performance of multi-asset trend strategies relative to static trend strategies, especially in months after asset turning points.

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 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 capable of exploiting this relationship and recovering much of the loss experienced by static-window trend following.

Although our focus is on trends in the time series of individual assets at different horizons, our study shares some themes with the cross-sectional momentum literature. Han, Zhou, and Zhu (2016) use information in past stock prices across several different time horizons to infer trends in the cross section of US stocks and develop a model to study how the predictive content of past prices may concentrate in different horizons at different points in time. We employ only two elementary past return signals and analyze how they capture predictive content for trend shifts of many assets in other asset classes and equity markets in addition to US equities.

Our results have practical implications for synthesizing investment signals. Trend following is a widespread investment approach that falls under the umbrella of technical analysis, which entails forecasting future asset prices using past data. Price path charts and related price indicators have a long history of use by practitioners, which has only increased with the spread of computing power and rules-based trend following.[9] Covel (2004) advocates exclusive use of technical analysis principles in his influential study of trend following and emphasizes the use of trend following by successful hedge funds. However, there are many technical indicators and signals to choose from. The information quality of different signals varies over time and the question arises of how to weigh different signals to take effective trading actions. For example, what is the optimal lookback horizon for a momentum strategy and how can we detect whether that horizon changes through time? Our analysis provides concrete examples of how agreement or disagreement between simple momentum signals of different horizons carries predictive information for future returns across a variety of assets and asset classes and highlights the economic significance that higher frequencies of disagreement have for trend-following performance.

Data and Turning Points

Data. We use monthly returns for 43 futures markets across three major asset classes: 11 equity indices, 8 bond markets, and 24 commodities. Our data begin in January 1980 for some of the assets. For all others, we add an asset into the analysis when its return data become available. Our evaluations focus on the period 1990–2022, for which we have enough return data to compute 12-month trend-following strategies for at least four assets in each asset class. Starting evaluations in 1990 is also for consistency with later analyses in which we use data before 1990 to warm up dynamic strategies for evaluation beginning in 1990. Our time series of returns is based on holding the front-month contract, then swapping into a new front contract as the expiration date of the held contract approaches. See Appendix A for more details.

Time-Series Momentum. For each of the 43 markets, we construct a binary time-series momentum strategy following the methodology described by Goulding, Harvey, and Mazzoleni (2023). 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.[10] This simple design is similar to that used by Goyal and Jegadeesh (2017) and Huang et al. (2020). Note that we do not scale the momentum signal by trailing volatility as do Moskowitz, Ooi, and Pedersen (2012), and we do not exponentially weight past prices.[11] 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 Goulding, Harvey, and Mazzoleni (2023). For each of the 43 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, its slow and fast momentum signals for month m are the averages of its monthly excess returns in preceding months:

$$x_{m,\mathrm{SLOW}} = \frac{r_{m-1} + r_{m-2} + \cdots + r_{m-k_{\mathrm{SLOW}}}}{k_{\mathrm{SLOW}}}, \tag{1}$$

$$x_{m,\mathrm{FAST}} = \frac{r_{m-1} + r_{m-2} + \cdots + r_{m-k_{\mathrm{FAST}}}}{k_{\mathrm{FAST}}}, \tag{2}$$

where k_{SLOW} and k_{FAST} are the number of lookback months, respectively, with $k_{\mathrm{SLOW}} > k_{\mathrm{FAST}}$. For example, SLOW may be the average of the prior 12 months of returns ($k_{\mathrm{SLOW}} = 12$), while FAST may be the average of the prior 2 months of returns ($k_{\mathrm{FAST}} = 2$). 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 an asset 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).[12] If a trend break has indeed occurred, then slower signals prescribe bad bets (e.g., shorting the market based on an older downward trend when the market is recently trending up). If, however, 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 relative to static trend following. For now, we focus on the within-year relationship between annual turning points and trend returns.

For each asset, we define the number of turning points per year as:

$$\mathrm{TP}_y = \text{number of months } m \text{ in year } y \text{ such that } \operatorname{sign}(x_{m,\mathrm{SLOW}}) \neq \operatorname{sign}(x_{m,\mathrm{FAST}}). \tag{3}$$

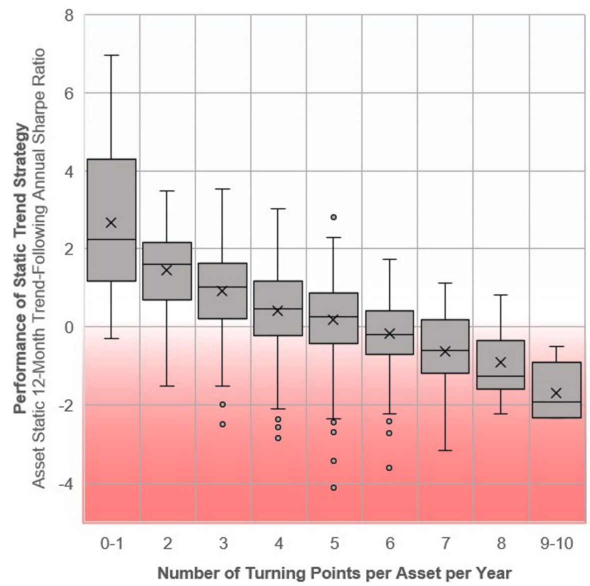
For each asset, TP_y is an integer between 0 and 12, which counts the number of months within year y that were turning-point months for the asset.

Turning Points and Static Trend. In Figure 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 33-year period 1990–2022. 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., $k_{SLOW} = 12$ and $k_{SLOW} = 1$ for all assets). 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.[13] There are 1,258 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 "×." 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.

Figure 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.[14] The figure also shows how costly turning points can be for trend following. For assets with six or more turning points within a year, typical (median) returns to static trend following are negative. For assets with eight or more turning points within a year, the vast majority of returns to static trend following are negative with annualized Sharpe ratios below −1.25 for the median asset.

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 Figure 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 Figure 1 vanishes if we replace the number of turning points by bins of asset volatilities (see Figure B.1 in Appendix B). Third, the number of turning points per asset per year is approximately uncorrelated with return volatility: 0.07 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.

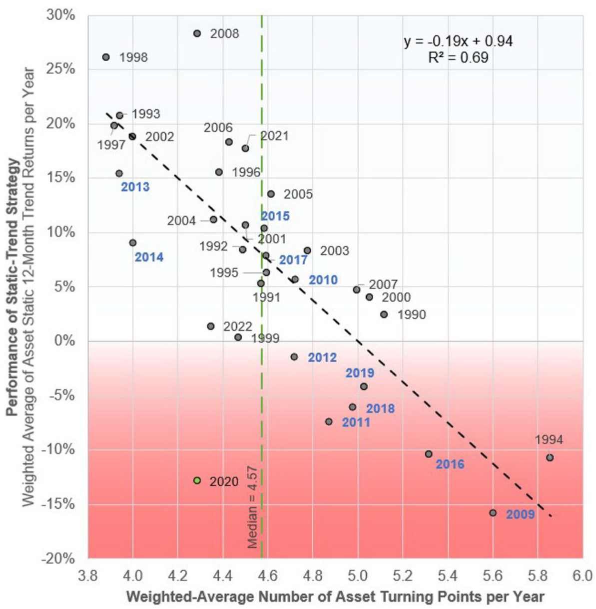
Figure 1. Static-Trend Performance vs. Number of Turning Points per Asset per Year (January 1990 to December 2022)



Note. 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 an asset's annual excess return from trend following divided by an asset's annualized realized monthly volatility of trend following. There are 1,258 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 ≤1.5 times the IQR and down from the bottom of the box to the smallest data point >1.5 times the IQR. We consider values outside this range as outliers, represented by dots.

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 Figure 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 by allocating equal weight to each asset's value within its asset class and equal weight to each asset class across the three asset classes. For example, we assign 1/72 weight to each of the 24 commodities (1/24 to each commodity and 1/3 to commodities overall). Similarly,

Figure 2. Multi-Asset Static-Trend Portfolio Performance vs. Weighted-Average Number of Asset Turning Points per Year (January 1990 to December 2022)



Note. 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. For example, we assign 1/72 weight to each of the 24 commodities (1/24 to each commodity and 1/3 to commodities overall). We normalize portfolio returns to 10% annualized monthly volatility over the sample. The labels corresponding to the expansion years after the GFC (2009–2019) are in blue. The dot corresponding to the outlier of 2020 due to COVID-19, excluded from the calculation of the trend line, is in green. The vertical green dashed line at 4.57 indicates the median annual weighted-average number of asset turning points.

we construct a multi-asset static trend portfolio return as the equally weighted average of individual asset static trend-following returns.[15]

Similar to Figure 1, Figure 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 = 0.69 and slope −0.19) quantifies the negative relationship.[16] A one–standard deviation increase in the weighted average number of asset turning points (+0.47, say, from 4.57 to 5.04) translates to approximately 8.9 percentage points lower annual return, which is economically significant relative to the 10% annualized volatility level over the sample.

Figure 3 shows the distribution of the number of turning points per year per asset across all 43 assets over the period 1990–2022 split into the post-GFC expansion period, 2009–2019, and all other years. The distribution of turning points in 2009–2019 exhibits an upward shift relative to the distribution in other years.[17] This phenomenon is also present in Figure 2. Nine of the 11 post-GFC expansion years (highlighted in blue) have a weighted average number of turning points that rank at or above the median for the 33-year period (blue-labeled dots right of the vertical dashed line in Figure 2). Given the negative relationship between the number of turning points and trend-following performance highlighted in Figures 1 and 2, this shift can help explain the deterioration of trend-following performance following the GFC.

Turning Points and Dynamic Trend. In this section, we adapt the dynamic trend-following methodology of Goulding, Harvey, and Mazzoleni (2023) to each asset in our universe of 43 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:

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

Note that the union of correction and rebound phases equals turning-point phases of our earlier definition: $\text{sign}(x_{m,\text{SLOW}}) \neq \text{sign}(x_{m,\text{FAST}})$ if and only if s_m = correction or rebound.[18] We also define the returns to the slow and fast momentum strategies for each asset in each month as follows:

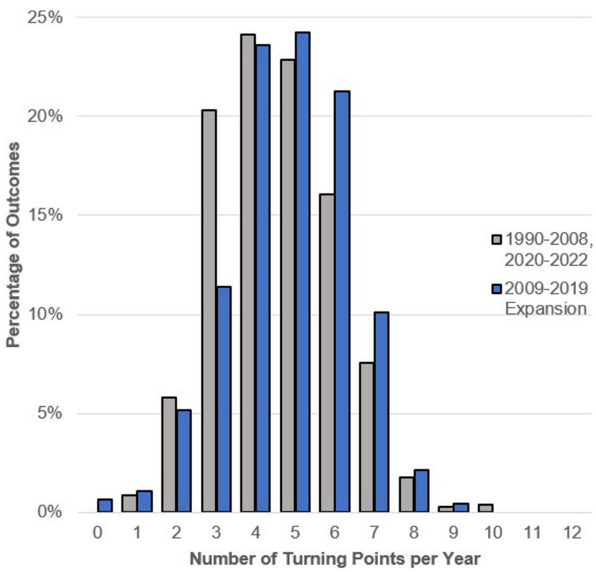
$$r_{m,\text{SLOW}} = \begin{cases} r_m, & \text{if } x_{m,\text{SLOW}} \geq 0, \\ -r_m, & \text{if } x_{m,\text{SLOW}} < 0, \end{cases} \tag{5}$$

$$r_{m,\text{FAST}} = \begin{cases} r_m, & \text{if } x_{m,\text{FAST}} \geq 0, \\ -r_m, & \text{if } x_{m,\text{FAST}} < 0. \end{cases} \tag{6}$$

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

Figure 3. Upward Shift of Turning-Point Distribution in Post-GFC Expansion: Empirical Distribution of Number of Asset Turning Points per Year (January 1990 to December 2022)



Note. 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. The 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 as a percentage of all category outcomes in that time range. There are 792 observations from 1990 to 2008 and from 2020 to 2022 and 466 observations from 2009 to 2019.

way that can vary after observing different market states as follows:

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

Each mixing parameter (a_{Co} or a_{Re}) is a mixing weight placed on the fast strategy—after observing either a correction or rebound, respectively. Behavior after bull and bear states 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 January 1990, our sample is reduced by the number of 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 $a_{\mathrm{Co}} < 0.5,$ 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 $a_{\mathrm{Re}} > 0.5,$ 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 0.5.

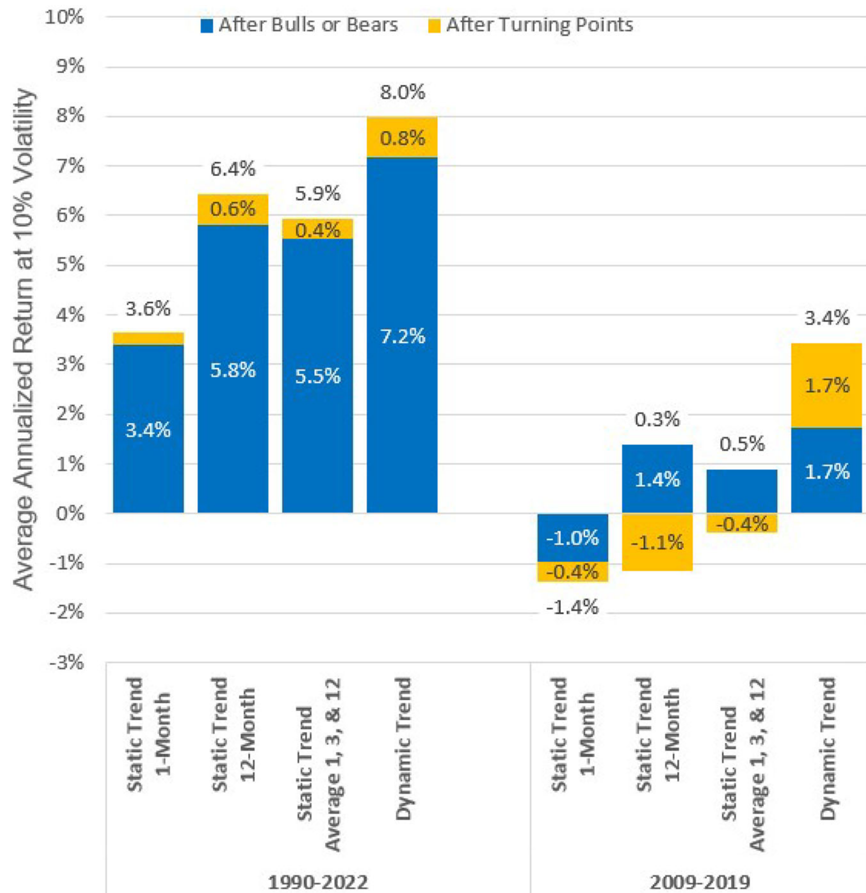
This strategy is implementable as a trading strategy with no look-ahead bias. We form the multi-asset dynamic trend portfolio as follows. Using the equations described above for each asset, at the beginning of each month we blend the asset's slow and fast trend strategies according to the observed market 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 an asset's 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 main empirical analysis.[19]

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.

In Figure 4, we compare the annualized monthly returns of this multi-asset dynamic-trend portfolio alongside the multi-asset static 12-month-trend portfolio, with each

Figure 4. Average Annualized Return Decomposition for Multi-Asset Trend-Following Portfolios Using Static-Trend or Dynamic-Trend Strategies for Each Asset: 1990–2022 and post-GFC Expansion 2009–2019



Note. 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_{Co} after corrections and a_{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.

portfolio normalized to 10% volatility over the stated sample periods.[20] Figure 4 also shows the decomposition of these returns into returns following bull or bear phases and returns following turning points, corrections, or rebounds. Multi-asset static 12-month trend following generates approximately a 6.4% annualized average return over the full evaluation period, 1990–2022, yet only 0.3% in the post-GFC expansion period, 2009–2019. In the post-GFC expansion period, its gains after bull or bear phases are largely offset by its losses after turning points.

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. Because it operates at lower volatility, when it is scaled to have 10% annualized volatility, the dynamic trend portfolio generates higher average returns after bull or bear phases relative to static strategies at the same volatility scale. Average returns of both static and dynamic methods decreased in post-GFC expansion years; however, dynamic trend generated 3.4%

average returns, which was well above the 0.3% generated by static 12-month trend. Moreover, nearly half of the dynamic gains are from returns harvested after turning points. We draw similar inferences from the alternative static specifications using the faster static 1-month trend following portfolio or the blend of static 1-, 3-, and 12-month trend following strategies as studied by Babu et al. (2020a). Faster static trend strategies or static blends of static trend strategies struggle to generate returns after turning points, particularly following the GFC.

Conclusion

Trend-following strategies at the monthly trading frequency have experienced notably weaker performance in the expansion period after the global financial crisis of 2008 compared with the decades before. 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. The years following the GFC have exhibited more turning points across assets and asset classes and, therefore, fewer periods of sustained uptrend or downtrend, in which trend following tends to be 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 allows the momentum speed (fast or slow) to vary through time. This dynamic solution focuses on addressing performance after turning points. We demonstrate that dynamic trend following can harvest returns after turning points, returns that might have been lost under standard static 12-month trend following.

Our results have implications for the allocation of capital to trend following in different assets. In our multi-asset trend portfolio analysis, we equally weight each asset and asset class for simplicity and comparability of portfolios across static and dynamic trend strategies. However, different commodities, different bond markets, and different equity markets experience heterogenous frequencies of turning points, which in turn could be utilized to vary exposure more effectively to trend following of different assets or asset classes. Moreover, if markets settle back into pre-GFC turning-point dynamics, then improved multi-asset trend-following opportunities may arise. We defer the study of these potential applications to future research.

Notes

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; Gutierrez and Kelley, 2008). This phenomenon is stable across assets and countries (Rouwenhorst 1998; Griffin, Ji, and Martin 2003; Israel and Moskowitz 2013; Asness, Moskowitz, and Pedersen 2013). Studies of the merits of trend following and time-series momentum investing, in particular, include the following: Cutler, Poterba, and Summers (1991), Silber (1994), Fung and Hsieh (1997, 2001), Erb and Harvey (2006), Moskowitz, Ooi, and Pedersen (2012), Menkhoff et al. (2012), Baltas and Kosowski (2013), Hurst, Ooi, and Pedersen (2013), Baltas and Kosowski (2015), Levine and Pedersen (2016), Georgopoulou and Wang (2017), Hurst, Ooi, and Pedersen (2017), Ehsani and Linnainmaa (2022), Goulding, Harvey, and Mazzoleni (2023), Gupta and Kelly (2019), and Babu et al. (2020a, 2019b).

2. See Goulding, Harvey, and Mazzoleni (2023).

3. The *cross-sectional* momentum literature has explored themes related to market cycles and turning points (Cooper, Gutierrez, and Hameed 2004; Daniel, Jagannathan, and Kim, 2012; Daniel and Moskowitz, 2016). Cooper, Gutierrez, and Hameed use a slow trailing 3-year return to define two market states: "up" and "down." Daniel, Jagannathan, and Kim (2012) use a two-state hidden Markov model of unobserved "turbulent" and "calm" states to predict crashes in cross-sectional momentum portfolios. Daniel and Moskowitz (2016) study cross-sectional momentum crashes and recoveries and propose a dynamic cross-sectional weighting strategy. Goulding, Harvey, and Mazzoleni (2023) use the intersection of slow and fast trailing return signals to characterize four market states and to define trend turning points.

4. A 12-month lookback window is the standard window length for time-series momentum analyzed in the literature (Moskowitz, Ooi, and Pedersen, 2012 and Huang et al., 2020), 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 lookback windows (e.g., Babu et al. 2020a). We look at such alternatives in a later section.

5. Goulding, Harvey, and Mazzoleni (2023) focus exclusively on equity indices and do not explore the role of turning-point frequency.

6. Performance of the Société Générale (SG) Trend Index, an equally weighted index of major trend-focused funds, launched 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 April 2015 to January 2019. Likewise, the annualized Sharpe ratio of a hypothetical multi-asset portfolio of 12-month trend-following strategies with monthly rebalancing decreased substantially in the post-GFC expansion period—see static multi-asset trend-following performance in later sections.

7. The 11-year post-GFC expansion period ended with the brief COVID recession event of 2020, which experienced a lower number of turning points but of higher severity. The two years of subsequent expansion (2021–2022) exhibit some reversion of turning-points frequency to pre-GFC levels. In Appendix E, we report performance statistics of several trend-following strategies over various sample periods: Full sample 1990–2022; through GFC 1990–2008; post-GFC 2009–2022; and post-GFC expansion 2009–2019.

8. This approach is distinct from moving average crossovers, which Levine and Pedersen (2016) show are essentially equivalent to *static* blends of time-series momentum strategies. Hurst, Ooi, and Pedersen (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.

9. See Han et al. (2021) for a survey of the literature on technical analysis including trend following.

10. 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 rate of market borrowing for institutions.

11. Volatility scaling may have a distinct effect from time-series momentum (e.g., Kim, Tse, and Wald 2016; Moreira and Muir 2017; Harvey et al., 2018; Goulding, Harvey, and Mazzoleni 2023) and we seek to avoid intermixing the two mechanisms.

12. 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.

13. Performance is gross of costs to roll contracts or of any transaction costs. In Appendix E, we report the turnover of various trend strategies including static 12-month trend and a dynamic trend strategy developed in a later section. The dynamic trend strategy incurs more turnover than the static trend strategy. Nevertheless, for average transaction costs below 29 basis points—a comfortable upper bound for these assets—the dynamic strategy remains more profitable than the static strategy.

14. In our sample, three asset-years have zero turning points, seven asset-years have 9 or 10 turning points, and no asset-years have 11 or 12 turning points.

15. 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.

16. In the estimation of the trend line, we exclude 2020 as an outlier due to COVID-19. Our turning-point measure captures frequency but not severity of trend breaks. In this outlier year, we find a lower-than-average number of turning points but a larger magnitude of market shift. If this year were included, the trend line would still exhibit a strong negative relationship ($R^2 = 0.56$ and slope -0.18).

17. The average increases to 4.80 asset turning points per year relative to 4.54 in other years. We can see in Figure 2 that the number of turning points in years 2020–2022 reverted to near typical levels, with 2020 being an outlier in terms of its relationship with performance. In 2020, investors in static 12-month trend would have experienced a relatively high loss despite a lower-than-average number of turning points.

18. 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.

19. In Appendix D, we show results of the dynamic approach using 1- and 12-month lookback horizons for fast and slow signals, respectively, and obtain consistent conclusions. Use of the 2-month signal highlights 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 bonds while the disagreement between 1-month and 12-month trend directions might be more informative for equities. Likewise, the diversification properties across different assets may also vary with the choice of slow and fast signals.

20. In Appendix E, we report additional portfolio statistics over various subsamples for each strategy shown in Figure 4, but without normalized volatilities.

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Appendices

Appendix A. Data Details

We use monthly returns from Barchart for 43 futures markets. Our data for these markets run through to December 2022 with varying start dates (listed in the asset class subsections below in parentheses after the index name). Our evaluations focus on the period 1990–2022, for which we have enough return data to compute 12-month trend-following strategies for at least four assets in each asset class. We use data prior to January 1990, where available, to warm up estimates used in dynamic strategies and we begin all evaluations in January 1990 for consistency. Roll schedules are based on liquidity of contracts, with the front contract being most liquid. Our universe consists of contracts that are the front contract and are rolled out to next nearest contract at the beginning of the expiration month of the contract.

Equity Futures. Our equities universe includes 11 developed market indices: Australia (ASX SPI 200 Index, June 2000), Canada (S&P/TSX 60 Index, October 1999), France (CAC40 10 Index, September 1988), Germany (DAX Index, December 1990), Hong Kong (Hang Seng Index, June 1986), Italy (FTSE/MIB Index, June 2004), Japan (Nikkei 225 Index, October 1988), Netherlands (AEX Index, December 1995), Sweden (OMXS30 Index, March 2005), United Kingdom (FTSE 100 Index, June 1984), and United States (S&P 500 Index, October 1997).

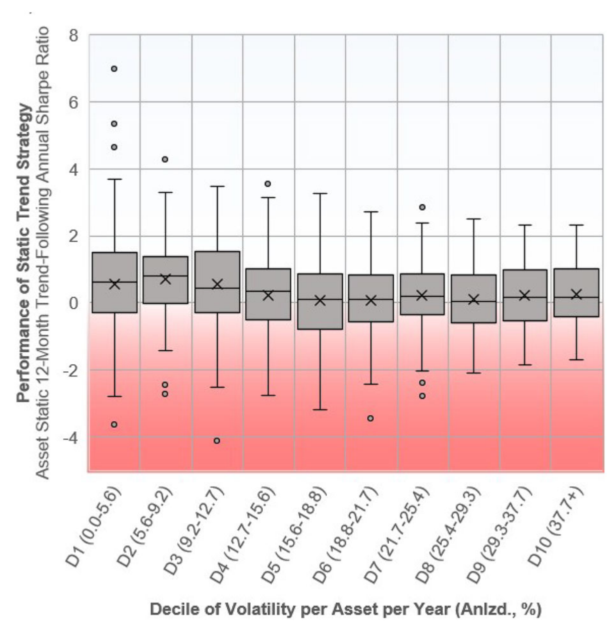
Bond Futures. Our bond universe includes 8 developed market indices: Australia (Australia 10Y Bond, January 1985), Canada (Canada 10Y Bond, October 1989), France (Euro-OAT Bond, May 2012), Germany (Euro-Bund Long Term, January 1991), Italy (EURO-BTP Bond, November 2009), Japan (Japan 10Y Bond, November 1985), United Kingdom (Gilt Long Bond, December 1982), and United States (US Treasury 10Y Bond, June 1982).

Commodity Futures. Our commodities universe includes 24 commodities across 6 sectors (energy, grains, industrial metals, livestock, precious metals, and softs): Aluminum (August 1997), Brent Crude (August 1989), Cocoa (January 1980), Coffee (January 1980), Copper (January 1986), Corn (January 1980), Cotton (January 1980), Feeder Cattle (January 1980), Gasoil (July 1986), Gasoline (January 1985), Gold (January 1980), Heating Oil (January 1980), Kansas Wheat (January 1980), Lead (November 1997), Lean Hogs (January 1980), Live Cattle (January 1980), Natural Gas (May 1990), Nickel (August 1997), Silver (January 1980), Soybeans (January 1980), Sugar (January 1980), Wheat (January 1980), WTI Crude (April 1983), and Zinc (August 1997).

Appendix B. Static-Trend Performance vs. Volatility

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

Figure B.1. Static-Trend Performance vs. Volatility Decile per Asset per Year (January 1990 to December 2022)



Note. For each asset in each calendar year, we calculate its annualized monthly return volatility. We group all asset-year volatilities into 10 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 asset's annual excess return from trend following divided by the asset's annualized realized monthly volatility of trend following. 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 ≤1.5 times the IQR and down from the bottom of the box to the smallest data point >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 Goulding, Harvey, and Mazzoleni (2023), 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. We use the first two letters of each market state name as an abbreviation—{Bu}ll, {Be}ar, {Co}rrection, and {Re}bound—where the definition of each state is given in (4). For each asset, its mixing parameters for month *m* are computed as follows:

$$a_{Co} = \frac{1}{2}\left(1 - \frac{1}{C}\cdot\frac{AVG[r|Co]}{AVG[r^2|Co]}\right), \tag{8}$$

$$a_{Re} = \frac{1}{2}\left(1 - \frac{1}{C}\cdot\frac{AVG[r|Re]}{AVG[r^2|Re]}\right), \tag{9}$$

$$\begin{aligned} C = & \frac{FREQ[Bu]}{FREQ[Bu\,or\,Be]}\cdot\frac{AVG[r|Bu]}{AVG[r^2|Bu\,or\,Be]} \\ & - \frac{FREQ[Be]}{FREQ[Bu\,or\,Be]}\cdot\frac{AVG[r|Be]}{AVG[r^2|Bu\,or\,Be]} \end{aligned} \tag{10}$$

where AVG$[r|s]$ and AVG$[r^2|s]$ denote the average return and average squared return, respectively, over all months prior to month *m* in which the market state was *s* and FREQ$[s]$ denotes the frequency of months prior to month *m* in which the market state was *s*. The scalar *C* in (10) 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* is typically positive and used as a normalizer in (8) and (9).

Each asset's mixing parameter (a_{Co}, a_{Re}) is the mixing weight on the fast strategy. In our historical simulations, we update each mixing parameter estimate every 30 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 January 1990, 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 $a_{\mathrm{Co}} < 0.5$, 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 $a_{\mathrm{Re}} > 0.5$ reflecting a tilt toward FAST in proportion to the volatility of those returns.

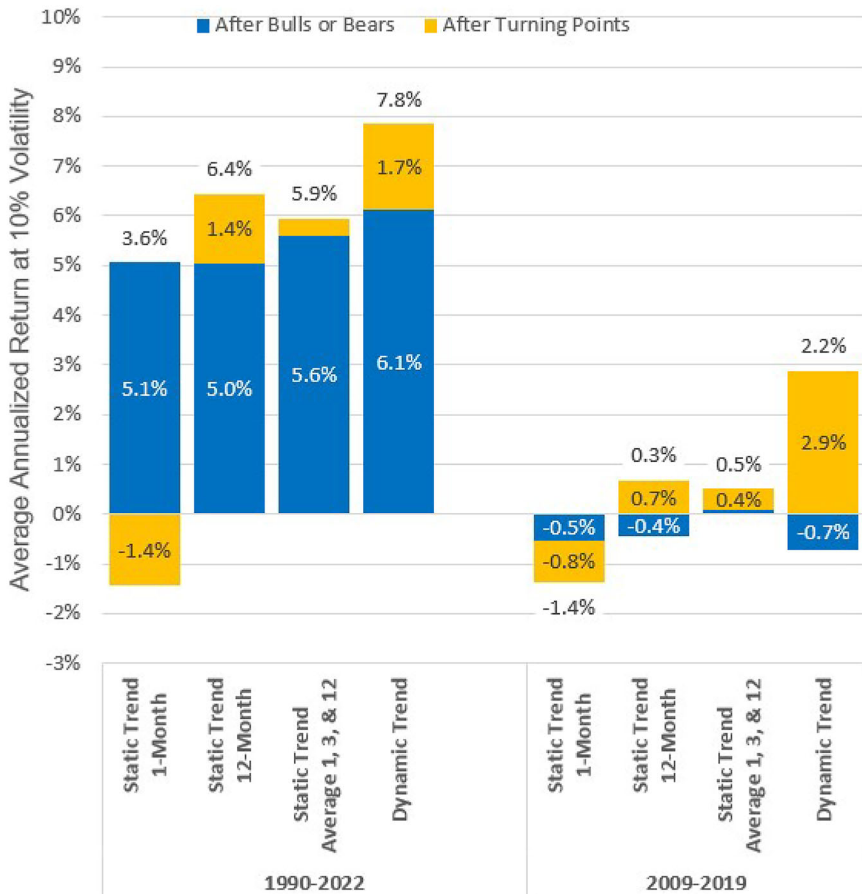
Appendix D. Return Decomposition Using 1- and 12- Month-Based Turning Points

In Figure D.1, we compare the annualized monthly returns of the multi-asset dynamic-trend portfolio alongside the multi-asset static 12-month trend portfolio, with each portfolio normalized to 10% volatility over the stated sample periods, using 1- and 12-month lookback periods for fast and slow signals, respectively. This robustness analysis contrasts with our main dynamic-strategy analysis, which used 2- and 12-month lookback periods, respectively, to define market states and turning points. Nevertheless, the key takeaways are similar. Multi-asset static 12-month trend following generates a lower average return compared to the multi-asset dynamic-trend-following portfolio over the full evaluation period, 1990–2022, as well as over the post-GFC expansion period, 2009–2019. Moreover, during the post-GFC expansion period, in which turning points increase in frequency, the dynamic portfolio does a better job harvesting returns after turning points than does the static portfolio, although both portfolios struggle to harvest returns after periods following bulls or bears. The static 1-month portfolio and the 1-, 3-, and 12-month blended portfolios also underperform the dynamic portfolio with respect to harvesting returns after turning points.

Appendix E. Trend Strategy Statistics

In this section, we report additional portfolio statistics over various subsamples for each strategy shown in Figure 4, but without normalized volatilities. Panel A of Table E.1 reports statistics for the full sample period, 1990–2022, which corresponds to the columns on the left half of Figure 4. Without any volatility adjustments, compared to the static 12-month trend strategy, the dynamic trend strategy generates both higher average excess returns and lower volatility, resulting in a higher Sharpe ratio. Moreover, the dynamic strategy exhibits lower drawdown risk, having −13.2% worst drawdown compared to −18.8% of the static 12-month strategy. Because positions in the SLOW and FAST legs of the dynamic strategy (as well as the Avg. 1, 3, 12

Figure D.1. Average Annualized Return Decomposition for Multi-Asset Trend-Following Portfolios Using Static-Trend or Dynamic-Trend Strategies for Each Asset: 1990–2022, and post-GFC Expansion, 2009–2019



Note. 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. Bull = its trailing 12- and 1-month returns are positive (non-negative); correction = its trailing 12-return is positive (non-negative), but its trailing 1-month return is negative; bear = its trailing 12- and 1-month returns are negative; and rebound = its trailing 12-month return is negative, but its trailing 1-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 1-month static strategies using the mixing parameter on the 1-month strategy of a_{Co} after corrections and a_{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.

strategy) occasionally offset, the dynamic strategy maintains lower gross leverage—i.e., the sum of the absolute values of its asset positions—compared to the static 12-month strategy. Finally, blending the SLOW and FAST strategies increases the turnover of the dynamic strategy (as well as the Avg 1, 3, 12 strategy) relative to the static 12-month strategy. However, the increase in turnover is offset with an increase in average excess return as well as lower volatility and gross leverage. For average transaction costs below 29 basis points—a comfortable upper bound for these assets—the dynamic strategy remains more profitable than the static 12-month strategy. Notably, the turnover of the dynamic strategy is lower than that of the Avg 1, 3, 12 strategy.

Dynamic trend also exhibits performance improvements relative to static trend strategies in notable subsamples. Panel B of Table E.1 reports statistics

Table E.1. Trend Strategy Statistics in Various Subsamples

Panel A Full Sample: 1990–2022	Static Trend 1-Month	Static Trend 12-Month	Static Trend Avg. 1, 3, 12	Dynamic Trend
Avg. Excess Return (Anlzd., %)	2.4	4.2	3.2	4.7
Volatility (Anlzd., %)	6.5	6.5	5.4	5.9
Sharpe Ratio	0.36	0.64	0.59	0.80
Worst Drawdown (%)	−17.4	−18.8	−12.5	−13.2
Average Gross Leverage (%)	100	100	68	85
Turnover (Anlzd., %)	1135	229	600	399

Panel B Through GFC: 1990–2008	Static Trend 1-Month	Static Trend 12-Month	Static Trend Avg. 1, 3, 12	Dynamic Trend
Avg. Excess Return (Anlzd., %)	4.0	7.0	5.1	7.3
Volatility (Anlzd., %)	6.6	6.5	5.7	6.0
Sharpe Ratio	0.61	1.07	0.90	1.20

Panel C Post GFC: 2009–2022	Static Trend 1-Month	Static Trend 12-Month	Static Trend Avg. 1, 3, 12	Dynamic Trend
Avg. Excess Return (Anlzd., %)	0.1	0.4	0.6	1.2
Volatility (Anlzd., %)	6.2	6.3	4.9	5.5
Sharpe Ratio	0.01	0.06	0.13	0.22

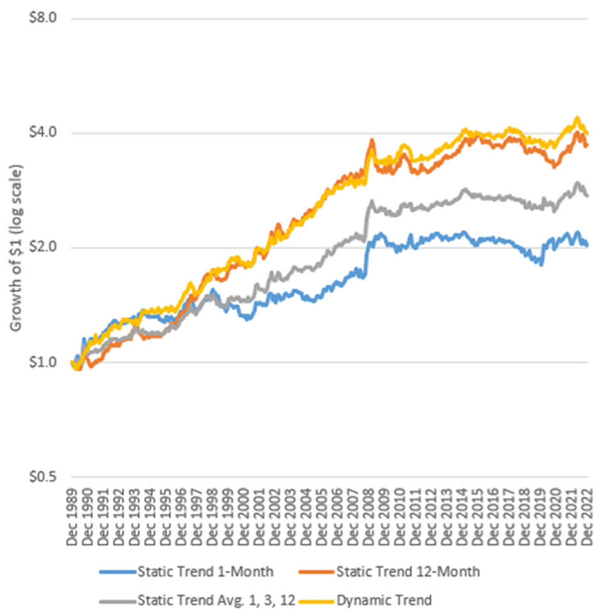
Panel D Post GFC Expansion: 2009–2019	Static Trend 1-Month	Static Trend 12-Month	Static Trend Avg. 1, 3, 12	Dynamic Trend
Avg. Excess Return (Anlzd., %)	−0.7	0.2	0.2	1.8
Volatility (Anlzd., %)	5.1	6.2	4.2	5.3
Sharpe Ratio	−0.14	0.03	0.05	0.34

Note. This table reports statistics for each trend strategy shown in Figure 4 over various sample periods, but returns are not scaled to achieve 10% annualized volatility.

for the period through the GFC, 1990–2008. Panel C reports statistics for the post-GFC period including COVID and post-COVID-years, 2009–2022. Panel D reports statistics for the post-GFC expansion period, 2009-2019. In all subsamples, including Panel A, the dynamic strategy exhibits the highest Sharpe ratio and higher average returns plus lower volatility compared to the static 12-month strategy. Dynamic trend also performs favorably relative to static 12-month trend during the COVID event year of 2020: −4.9% for dynamic trend vs. −8.5% for static 12-month trend.

Figure E.1 plots the growth of $1 investment in each of the trend-following strategies of Table E.1 over the full sample 1990–2022. Dynamic trend is less volatile, and experiences less severe drawdowns compared to static 12-month trend, while accumulating similar or better wealth levels over the sample period.

Figure E.1. Dollar Growth of Multi-Asset Trend-Following Portfolios Using Static-Trend or Dynamic-Trend Strategies for Each Asset: 1990–2022



Note. The figure shows the dollar growth of each trend strategy shown in Figure 4 over the full sample period 1990–2022, but returns are not scaled to achieve 10% annualized volatility.