You Can’t Always Trend When You Want

Abhilash Babu, Brendan Hoffman, Ari Levine, Yao Hua Ooi, Sarah Schroeder, Erik Stamelos*

Abstract

We present a novel framework to decompose the drivers of trend-following performance into (i) the magnitude of market moves, (ii) the strategy’s ability to profit from those market moves, and (iii) the degree of diversification across markets. This framework allows us to examine why trend performance has been below the strategy’s long-term average return during the current decade. We find that the lower performance of the strategy is neither explained by (ii) nor (iii): trend following has continued to profit from market moves and benefit from diversification. Instead, the primary explanatory factor is (i), namely that the average size of global market moves has been more muted than usual in the current decade. The fact that trend-following strategies continue to translate market moves into profits in a diversified manner suggests that trend-following investing may see stronger performance in market environments characterized by more pronounced movements in markets going forward.

* Abhilash Babu, Brendan Hoffman, Ari Levine, Yao Hua Ooi, Sarah Schroeder and Erik Stamelos are at AQR Capital Management. AQR Capital Management is a global investment management firm, which may or may not apply similar investment techniques or methods of analysis as described herein. The views expressed here are those of the authors and not necessarily those of AQR.

With special thanks to Lasse H. Pedersen for his insights and thoughtful guidance.

Introduction

Trend following is a long-established investing strategy that attracted significant research focus over the past several decades.[1] The strategy exhibited strong performance during the Global Financial Crisis of 2007-2009 but has gone through a significant drawdown recently, delivering lower returns in the current decade compared to history.[2] This prompts the question of whether the strategy's efficacy has changed, and what factors explain the divergence in recent performance and long-term results.

To answer that, we develop a framework that provides a novel understanding of the sources of trend-following performance. We use the framework to elucidate why trend-following performance has been muted in the current decade. Our approach builds on the trend-following strategy as defined in Hurst et al. (2013, 2017) and uses data from the late 1800s through 2018. The framework identifies and examines three main factors that explain excess returns to a trend-following strategy: (i) the magnitude of market moves, (ii) the *trend efficacy*, or the strategy's ability to translate a given market move into profits, and (iii) the degree of diversification within a trend-following portfolio. We evaluate these factors and quantify their impact on trend-following performance in the current decade versus the full sample.[3]

Our findings suggest that the lower returns in the current decade are due to fewer large moves across markets and are not explained by a decline in the strategy's ability to profit from market moves nor by a reduction in diversification across trends in the portfolio. The fact that trend-following strategies continue to translate market moves into profits in a diversified manner suggests that trend-following investing may see stronger performance in market environments characterized by more pronounced movements going forward.

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[1] Some of the original work on trend-following investing and hedge funds was due to Fung and Hsieh (1997, 2001), who showed that trend-following can help explain managed futures hedge fund returns. Additional research on trend following or time series momentum includes Moskowitz et al. (2012), Baltas and Kosowski (2013, 2015), Hurst et al. (2013, 2017), Georgopoulou and Wang (2016), Gupta and Kelly (2019), and Babu et al. (2019); other research on price trends includes Cutler, Poterba and Summers (1991), Silber (1994), Erb and Harvey (2006), Menkhoff, Sarno, Schmeling, and Schrimpf (2012); Levine and Pedersen (2016) provide a unified framework for all trend-following strategies. Time series momentum is related to cross-sectional momentum, which is seen in equities (Jegadeesh and Titman (1993), Asness (1994)) and global asset classes (Asness, Moskowitz, and Pedersen (2013)).

Estimates of assets of under management of dedicated trend followers point to at least $100 billion as of December 31, 2018 and may be meaningfully higher when considering assets managed by multi-strategy funds and exposures offered via bank products. The estimate of dedicated trend-following assets comes from eVestment.

[2] The SG Trend Index is an equal-weighted index of the largest trend-focused managers open to new investment, as determined by Société General. The SG Trend Index's performance peaked on April 13, 2015 and realized a -19.7% return from that date through December 31, 2018. From January 1, 2010 through December 31, 2018, the SG Trend Index realized an annualized Sharpe ratio of 0.05, versus a Sharpe ratio of 0.28 from the inception of the Index on January 1, 2000 through December 31, 2018. Longer-term historic performance for trend following is described in literature on the strategy, including Hurst et al. (2013, 2017).

[3] Cash rates are another factor that explain trend-following performance. In the current decade, the lower rates of return on cash were a contributor to lower total returns relative to previous years, given interest rates close to 0% in the U.S. and other economies for most of the period. The remainder of our analysis sets cash rates aside and reflects on trend-following's lower Sharpe ratio in the current decade.

Data and Preliminaries

Data

We use monthly returns as described in Hurst et al. (2017) for 67 markets across four major asset classes. The markets considered include: 29 commodities, 11 equity indices, 15 bond markets, and 12 currency pairs. We use a dataset comprised of daily futures prices going back as early as 1877. Futures prices based on manual transcription of the "Annual Report of the Trade and Commerce of the Chicago Board of Trade" extend through 1951. We use electronic data sets once they become available. Appendix A provides a detailed description of the respective data sources used for each market and time period.

From the data, we construct monthly time series based on end-of-month prices and returns. We construct a continuous time series for each market by assuming that when approaching expiration we simultaneously sell out of the currently-held futures contract and buy the next available contract.[4] We use prices at the close whenever available and use an average of high and low prices in the early portion of the data sample where closing prices are not available.

Time Series Momentum Strategies

We construct a trend-following strategy using the time series momentum methodology described in Hurst et al. (2017).[5] For each of the 67 markets described above, we construct 1-month, 3-month, and 12-month time series momentum signals. Each time series momentum signal is binary, such that a long position is taken for any market where the past return in that market over the relevant look-back horizon is positive and a short position is taken for any market where the past return is negative. As such, each signal always holds either a long or a short position in each market. The three time series momentum signals are then equally weighted to provide an aggregate view on each market at each portfolio rebalance, which occurs monthly.

Positions are sized according to their expected volatilities[6] such that each market in the portfolio has the same risk ex-ante, both to maintain diversification across markets with different volatility profiles and to limit the amount of concentration risk. Positions are then scaled in aggregate such that the portfolio maintains a 10% ex-

[4] For assets other than commodities, futures are not available back to 1877. For those assets, we use cash index returns financed at local short-term interest rates until futures become available.

[5] The trend-following strategy is an equal-weighted combination of 1-month, 3-month, and 12-month time-series momentum strategies for 67 markets dating back to 1880, rebalanced monthly and with positions equally sized according to volatility. The combined strategy has an ex-ante volatility target of 10% annualized. For more details on the strategy, please see Hurst, B., Y.H. Ooi, and L.H. Pedersen. "A Century of Evidence on Trend-Following Investing." *Journal of Portfolio Management,* Vol. 44, No. 1 (2017).

[6] We use rolling 3-year standard deviation of returns for each asset as the relevant risk metric for sizing positions.

ante annualized volatility target.[7] This ensures that the portfolio targets a consistent level of risk over time, even while the number of markets available and the correlations between them vary. At each rebalance, the portfolio is constructed using the full set of assets for which data is available.

Transaction costs for the portfolio are calculated from the aggregate change in position per asset each month. We compute costs based on recent-period averages per asset class and inflate them historically based on estimates from Jones (2002). While we account for transaction costs on trades based on changes in position size, we note that there may be other costs, including the costs of rolling futures contracts, which are not accounted for. Overall, transaction costs are estimated with a significant amount of uncertainty. Details are provided in Appendix B.

A Trend-Following Performance Decomposition Framework

Trend-following strategies are designed to take advantage of a tendency for financial markets to exhibit a predictable continuation of past returns. Large, prolonged moves in asset prices (both positive and negative) are associated with positive returns for trend followers; conversely, range-bound periods lead to negative trend performance. Large market moves tend to happen over time rather than overnight, giving trend followers the opportunity to position themselves to profit from the move. In contrast, if markets do not have large moves and instead are range-bound, trend followers tend to realize losses as their positioning is out of phase with market movements.

Our framework is based on an empirical linear relationship between the average magnitude of market movement (measured as an absolute Sharpe ratio) $\langle|SR|\rangle$[8], and the average of trend-following performance in each market $\langle SR_{Trend}\rangle$[9]:

[7] We use rolling 3-year standard deviation of returns and correlations as the relevant metrics for estimating portfolio ex-ante volatility and sizing positions.

[8] Where applicable, we use the symbol $\langle\cdot\rangle$ to denote a weighted average across assets and $\bar{\ }$ to indicate a time-weighted average.

Details in Appendix C.

[9] $\langle SR_{Trend}\rangle$ is the weighted average individual asset trend Sharpe ratio:

$$\langle SR_{Trend}\rangle = \sum_i \left(x^i * SR^i_{Trend}\right) \ for\ all\ assets\ i = 1, \dots, M$$

$$x^i = \frac{\sigma^i_{Trend}}{\sum_i \sigma^i_{Trend}} \ for\ all\ assets\ i = 1, \dots, M$$

$$SR^i_{Trend} = \frac{r^i_{Trend}}{\sigma^i_{Trend}} \ for\ all\ assets\ i = 1, \dots, M$$

where *r* is the strategy's excess return attributable to market *i* and *σ* is the realized (annualized) standard deviation of that market's excess monthly trend-following returns.

Equation 1

$$\langle SR_{Trend} \rangle = \underbrace{\alpha + \beta}_{\substack{Trend \\ Efficacy}} \underbrace{\langle |SR| \rangle}_{\substack{Market \\ Moves}}$$

Given $\langle SR_{Trend} \rangle$, we can express a trend-following portfolio's risk-adjusted excess-of-cash returns (or the portfolio Sharpe ratio SR^P_{Trend} by introducing a diversification multiplier *D* as follows:[10]

Equation 2

$$SR^P_{Trend} = \underbrace{D}_{\substack{Diversification \\ Multiplier}} \times \langle SR_{Trend} \rangle$$

Under the assumptions outlined in Appendix C, this decomposition is exact. The framework expresses trend-following performance as a function of three primary factors:

- **Average Magnitude of Market Moves**, $\langle |SR| \rangle$. This is a weighted average of absolute annualized risk-adjusted returns in traded markets. The absolute value is the relevant quantity because trend followers can profit from either rising or falling prices. This measure represents the average absolute Sharpe ratio of holding a long-only, fixed-notional investment.

- **Trend Efficacy**, (α, β). The parameters α and β reflect the degree to which trend following profited from a given size market move. Collectively, they translate the average magnitude of individual market risk-adjusted returns $\langle |SR| \rangle$ into average trend performance across individual markets $\langle SR_{Trend} \rangle$.

- **Diversification**, D. This reflects the fact that the risk-adjusted return of the trend-following portfolio is a multiple of the average risk-adjusted return from trend following an individual market, due to a lack of perfect correlation across assets.

We will now discuss each of these components in more detail. We will then apply this framework empirically to decompose performance in a given period into the three component parts. The technical details of the decomposition are provided in Appendix C.

[10] We calculate the trend strategy's portfolio Sharpe ratio as the strategy's average annual excess return *R*, and divide by the realized (annualized) standard deviation σ of the strategy's excess monthly trend-following returns over that period:

$$SR^P_{Trend} = \frac{R^P_{Trend}}{\sigma^P_{Trend}}$$

Average Magnitude of Market Moves

For each market *i* in each calendar year *t*, we define the magnitude of the market move as its absolute risk-adjusted (excess-of-cash) return, or absolute Sharpe ratio $|SR_t^i|$.[11] Risk-adjusting allows us to consider moves in low-volatility assets (*e.g.* Treasury futures) to those in high-volatility assets (*e.g.* crude oil futures). We further define the trend-following performance for each market in each year as the risk-adjusted returns to the trend-following strategy in that market, $SR_{Trend,t}^i$.[12]

In Exhibit 1, we plot the historical simulated performance of trend following against the absolute magnitude of the underlying market moves for each market in each year over the period 1880 to 2018. For visual simplicity, in Exhibit 2 we condense to one data point per calendar year, which represents the risk-weighted average trend-following performance across the asset universe against the risk-weighted average absolute magnitude of market moves in that given year. Exhibits 1 and 2 show there is a clear historical positive relationship between the absolute magnitude of moves in individual markets and the risk-adjusted returns of a hypothetical trend-following strategy.

Trend Efficacy

To quantify the relationship between market moves and trend-following profitability, we estimate a linear model:[13]

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[11] **We calculate the excess return *r* of the market *i* in each calendar year *t* and normalize by the realized (annualized) standard deviation σ of that market's excess monthly returns *r* in the respective calendar year *t*:**

$$SR_t^i = \frac{r_t^i}{\sigma_t^i}$$

We consider absolute values since trend following can benefit from both positive and negative moves in markets.

[12] We calculate the trend strategy's Sharpe ratio for asset *i* in year *t* using the same construction as for individual markets, applied to the trend-following returns in those markets.

[13] We regress the risk-adjusted excess returns to trend following for each market *i* in year *t* on the absolute risk-adjusted returns in market *i* in year *t*:

$$SR_{Trend,t}^i = \hat{\alpha} + \hat{\beta}|SR_t^i| + \varepsilon_t^i$$

The fitted model's coefficients $\hat{\alpha}$ and $\hat{\beta}$ then reflect the efficacy of trend following in capturing profits for a given magnitude market move. They differ slightly from the α and β in Equation 1 as detailed in Appendix C.

Because multi-period Sharpe ratios are weighted averages of single-period Sharpe ratios, we apply a weighted least squares regression to ensure that the weighted average error is zero. This ensures that single-period Sharpe ratios estimated from this model are consistent with realized multi-period Sharpe ratios, once aggregated across multi-period horizons. The results are not meaningfully different when using an ordinary least-squares regression methodology.

Trend followers can benefit from market moves over various time horizons. While a one-year horizon is not the only relevant horizon, it is an important one as it reflects the degree of large, prolonged market moves that are particularly relevant for medium-to-longer-term trend followers. For robustness, we also conducted our study using shorter time horizons and found similar results.

$$SR^i_{Trend,t} = \hat{\alpha} + \hat{\beta}\left|SR^i_t\right| + \varepsilon^i_t$$

This model captures how effectively trend-following strategies can translate market moves into trend-following returns. By estimating this model using data over specific subperiods, we can evaluate how trend efficacy varied through time.

Using this model on each asset and year pair, we can also aggregate across assets and years to relate the *average* trend performance across individual markets over a given time period $\langle SR_{Trend}\rangle$ to the *average* magnitude of the individual market moves over that period $\langle|SR|\rangle$, the result of which is Equation 1. The coefficients $\hat{\alpha}$ and $\hat{\beta}$ are proportional to the coefficients α and β in Equation 1, and therefore have the same interpretation. Details of the difference between coefficients and the full derivation of Equation 1 are shown in Appendix C.

Exhibit 3 shows the model fit for the full sample of data. The upward-sloping regression line shows that trend following has historically been able to translate large moves in markets into positive risk-adjusted returns. The negative intercept $\hat{\alpha}$ is expected because trend following historically realized losses in markets that exhibited little to no direction. The slope $\hat{\beta}$ is less than 1, indicating that trend performance improves as risk-adjusted directional moves in markets increase, but there is some loss due to dynamic positioning. A downward shift in the model fit (a lower $\hat{\alpha}$) and/or a more modest slope (a lower $\hat{\beta}$) would indicate lower expected trend performance for the same size market move. Conversely, a model fit that is shifted upward or more strongly upward sloping would indicate an improvement in trend efficacy.

Diversification

Equation 2 relates the average trend-following performance in each asset to the total portfolio Sharpe ratio via a diversification multiplier D. D is large (small) when the correlation between trend-following returns is low (high) and can vary substantially through time. Intuitively, it is related to the number of independent opportunities to capture trend profits.[14] If all markets in the portfolio are driven by a single underlying factor, we expect a smaller benefit from trading multiple markets than if all markets are functioning independently.

We determine risk-adjusted returns based on the average excess return to the specified asset in the specified period, normalized by the volatility of the excess returns to the asset in the specified period. While Sharpe ratios are traditionally calculated based on volatility in total returns (inclusive of cash returns), the volatility of cash returns is not substantial.

[14] D can be shown to be the quantity:

$$D_T = \left(\frac{\sum_i \sum_j \sigma^i_{Trend,T}\sigma^j_{Trend,T}}{\sum_i \sum_j \rho^{ij}_T \sigma^i_{Trend,T}\sigma^j_{Trend,T}}\right)^{1/2}$$

where ρ^{ij}_T is the realized correlation between trend-following returns in market *i* and *j* in period T.

Combining Equation 1 with Equation 2 yields the full decomposition of trend performance into these three parts. Splitting strategy performance into diversification, trend efficacy, and market moves allows us to isolate what may cause trend-following performance in a given period to differ from its long-term historical values.

Understanding the Drivers of Trend-Following Returns

Trend-following performance may differ in any subperiod versus the full sample due to variations in one or more of our three factors of interest. To understand differences in trend-following performance over time, we fit the model for each decade over the full sample. We then use our framework to decompose the difference in performance due to each of the three factors for each decade versus the full sample average of rolling decades from 1880 through 2018.[15]

To assemble the relevant factors, we segment the data by decade and fit the regression model to obtain a set of efficacy parameters $\{\alpha_T\}$ and $\{\beta_T\}$. We then compute for each subsample the diversification multiplier D_T as the ratio of the trend-following strategy's portfolio Sharpe ratio and the average per-asset trend-following Sharpe ratio, as shown in Equation 2. Last, for each decade we calculate the weighted average magnitude of market moves $\langle|SR|\rangle_T$.

We then use the three factors to decompose the difference in realized trend performance in each decade subsample versus the full sample average. We begin by replacing the average market moves in each decade $\langle|SR|\rangle_T$ by the full sample average $\overline{\langle|SR|\rangle_T}$, but keeping trend efficacy (α_T, β_T) and the diversification multiplier D_T constant. This tells us how trend following would hypothetically have performed if the magnitude of market moves had been equal to their full sample average values. We subsequently replace the trend efficacy parameters α_T, β_T with their full sample averages $\overline{\alpha_T}, \overline{\beta_T}$, keeping the average market move at its full sample average. This gives hypothetical trend performance using each decade's diversification, but long-term averages in efficacy and market moves. The impact of the difference in diversification between a decade subsample and the full sample average is derived from the difference in trend portfolio Sharpe ratios, less the estimated impacts due to differences in average market moves and trend efficacy.

Comparing hypothetical performance to actual performance yields the impact decomposition detailed in Appendix C. A positive (negative) impact indicates that the specified factor was more (less) favorable for trend performance in the corresponding decade than over the full sample. The decomposition allows us to determine whether market moves in the specified decade were usually pronounced (muted), trend following was more

[15] Details in Appendix C.

(less) effective at translating market moves into profitability, or whether trends were more (less) diverse. It is of course possible that some combination of the factors is responsible.

Exhibit 4 depicts the model fit over the current decade of 2010 – 2018 versus the full sample average of rolling decades. (Remember that this reflects hundreds of underlying data points averaged together for the purposes of visual simplicity.) We observe that the magnitude of market moves in the current decade falls closer to the left of the x-axis, indicating that indeed market moves have been small. This effect is replicated in Exhibit 5, which shows the distribution of the magnitude of market moves over the current decade against the distribution using data points from the full sample exclusive of the current decade.

In Exhibit 4, we also observe that the fitted line based solely on the current decade's observations (shown in yellow) is substantially similar to the full sample average, which suggests that trend efficacy has not been impaired. If trend efficacy had degraded, we would expect either a shift down (lower $\hat{\alpha}_T$) or a shallower slope (smaller $\hat{\beta}_T$), which is not observed. We note that when large market moves have occurred in the current decade, trend following was able to benefit, as in 2014.

Next we consider whether trend-following performance at the portfolio level has been hindered in recent years by a lack of diversification. There have been many anecdotal assertions that markets may have become more correlated after the Global Financial Crisis due to the heavy-handedness of central bank monetary policies affecting markets. However, the data do not bear this out. Exhibit 6 shows the full sample average diversification multiplier $\overline{D_T}$ for all rolling decades against the current decade D_T. The diversification multiplier for the trend-following strategy has not been materially different in recent history than in the full sample. We can therefore conclude that an unusual lack of diversification does not appear to explain trend-following's recent underperformance relative to history.

In Exhibit 7, we summarize the impact of the three factors for each decade in our sample. We do not observe any clear and persistent pattern in the impact of any of the factors over time. In the decades where trend following exhibited the strongest performance relative to the full sample, the magnitude of market moves carried a favorable impact. In the 1970s, the decade with the strongest trend performance, all three factors were favorable.

Exhibit 8 summarizes the results above for the current decade and explicitly shows the impact of the three explanatory factors on recent trend performance. Overall, the most significant factor affecting trend performance in the current decade was the muted magnitude of market moves, not diversification or trend efficacy. While this phenomenon could persist going forward, there is little reason to believe the fundamental dynamics of markets have changed permanently in recent years. Notably, when large market moves occurred, profitability was consistent with expectations based on the long-term evidence. These findings lead us to believe that the current decade's poor performance is not an indication of a change in the strategy's potential to profit from large market moves when they occur.

Conclusion

Our analysis provides a novel approach for evaluating trend-following performance over any given subperiod relative to the longer-term expectations established by existing literature. We analyze the difference in trend-following performance for each decade versus the full sample average and attribute that difference to three distinct factors: the magnitude of market moves, the efficacy of trend-following strategies at capturing profitability from market moves, and the degree of diversification across trends in a trend-following portfolio. Our results show that lower performance for trend following in the current decade is almost entirely explained by a lack of large risk-adjusted market moves (positive or negative). We do not find evidence of a material change in trend-following strategies' ability to translate market moves into trend-following performance, nor do we find evidence that trend followers have been less diversified. Looking ahead, this suggests that trend-following strategies should be able to deliver performance more in line with full sample results going forward if the size of market moves reverts to levels more consistent with the long-term historical distribution of returns.

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Appendix

Appendix A: Markets and Data Sources

We use historical returns data from 67 markets as seen in Figure A1. Below we list our data sources.

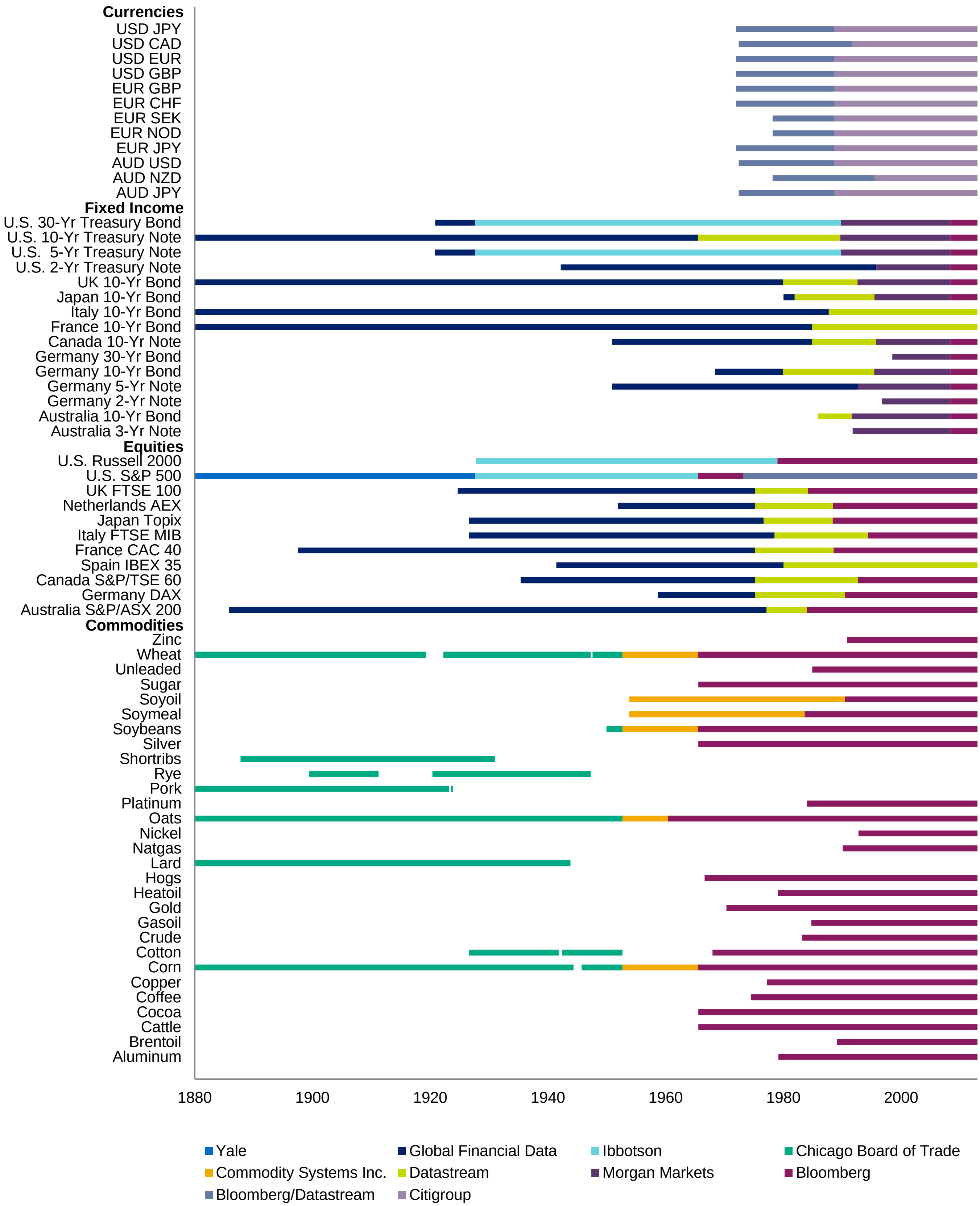
Equity Indices. The universe of equity index futures consists of the following 11 developed equity markets: SPI 200 (Australia), S&P/TSE 60 (Canada), CAC 40 (France), DAX (Germany), FTSE/MIB (Italy), TOPIX (Japan), AEX (Netherlands), IBEX 35 (Spain), FTSE 100 (U.K.), Russell 2000 (U.S.) and S&P 500 (U.S). Futures returns are obtained from Datastream and Bloomberg. We use MSCI country level index returns and returns from Ibbotson, Global Financial Data (GFD) and the Yale School of Management prior to the availability of futures returns.

Bond Indices. The universe of bond index futures consists of the following 15 developed bond markets: Australia 3-year bond, Australia 10-year bond, Euro Schatz (2-year), Euro Bobl (5-year), Euro Bund (10-year), Euro Buxl (30-year), Canada 10-year bond, Japan 10-year bond (TSE), Long Gilt, U.S. 2-year Note, Italian 10-year bond, French 10-year bond, U.S. 5-year note, U.S. 10-year note and U.S. long bond. Futures returns are obtained from Morgan Markets and Bloomberg. We use country level cash bond returns from Datastream, Ibbotson and Global Financial Data (GFD) prior to the availability of futures returns. We scale monthly returns from GFD and Ibbotson to a constant duration of 4 years, assuming a duration of 2 years for the U.S. 2-year note, 4 years for the U.S. 5-year note and German REX Index, 20 years for the U.S. long bond and 7 years for all other bonds.

Currencies. The universe of currency forwards covers the following 10 currencies: Australian dollar, Canadian dollar, German mark spliced with the euro, Japanese yen, New Zealand dollar, Norwegian krone, Swedish krona, Swiss franc, British pound and U.S. dollar. We use spot and forward interest rates from Citigroup to calculate currency returns going back to 1989 for all the currencies except for CAD and NZD, which go back to 1992 and 1996. Prior to that, we use spot exchange rates from Datastream and LIBOR short rates from Bloomberg to calculate returns.

Commodities. We use a data set of 29 different commodity futures that is significantly longer than what has been previously used in the literature. Where available, we use futures price data from Bloomberg. For periods before Bloomberg data is available, we use futures prices from Commodity Systems Inc. and a data set constructed from the historical records of the Chicago Board of Trade. The data from 1877 to 1951 was manually transcribed from the Annual Report of the Trade and Commerce of the Chicago Board of Trade (CBOT). To ensure accuracy, two independent data vendors transcribed the same data set, and their transcriptions were cross-verified to be mutually consistent. We note that, opening and closing prices were not recorded in the early part of the sample, so we use the average of high and low prices before closing prices are available. Finally, the roll schedule seeks to hold one the most liquid futures contracts across maturities. For example, each month in the hand collected data, we hold the nearest of the contracts whose delivery month is at least two months away.

Figure A1: Data sources by market and time period



Appendix B: Transaction Costs

The transactions costs used to simulate the net returns of the strategy are given in Table A1. These are based on proprietary estimates of average transaction costs for each of the four asset classes, including market impact and commissions, made in 2012. Further, the transaction costs are assumed to be twice as high from 1993 to 2002 and six times as high from 1880–1992, based on Jones (2002). We note that the transaction costs are estimated with a significant amount of uncertainty and do not include potential other costs such as the costs of rolling futures contracts.

Table A1. Simulated transaction costs

This table shows the assumed transaction costs for the time period 2003-2018. The transaction costs are assumed to be twice as high from 1993 to 2002 and six times as high from 1880–1992, based on Jones (2002).

Asset Class	Time Period	One-Way Transaction Costs (as a % of notional traded)
Equities	1880 – 1992	0.34%
	1993 – 2002	0.11%
	2003 – Present	0.06%
Fixed Income	1880 – 1992	0.06%
	1993 – 2002	0.02%
	2003 – Present	0.01%
Currencies	1880 – 1992	0.18%
	1993 – 2002	0.06%
	2003 – Present	0.03%
Commodities	1880 – 1992	0.58%
	1993 – 2002	0.19%
	2003 – Present	0.10%

Appendix C: Technical Appendix

Define a diversification multiplier D over time period T (T includes all years from t…$t+k$) such that the trend-following portfolio's Sharpe ratio measured over T is a multiple D_T of the average Sharpe ratio of trend following on an individual asset:

$$SR^{P}_{Trend,T} = D_T \times \langle SR_{Trend,T} \rangle$$

where

$$\langle SR_{Trend,T} \rangle = \sum_i \left(x^i * SR^i_{Trend,T} \right) \; for\ all\ assets\ i = 1, \ldots, M$$

$$x^i = \frac{\sigma^i_{Trend,T}}{\sum_j \sigma^j_{Trend,T}} \; for\ all\ assets\ i, j = 1, \ldots, M$$

Where applicable, we use the symbol $\langle \cdot \rangle$ to denote a weighted average across assets and $\bar{\cdot}$ to indicate a time-weighted average.

For a single asset *i* in a single year *t*, we model the asset's trend-following Sharpe ratio as a function of the asset's risk-adjusted absolute Sharpe ratio via a pooled regression over all years in *T* and *M* assets:[16]

$$SR^i_{Trend,t} = \hat{\alpha}_T + \hat{\beta}_T |SR^i_t| + \varepsilon^i_t$$

To aggregate single-year asset-level Sharpe ratios across a multi-year horizon *T*, we use the following relationship, where N^i_T is the number of years in a time period *T* with data available for asset *i*:

$$SR^i_{Trend,T} = \frac{1}{N^i_T} \sum_t \frac{\sigma^i_{Trend,t}}{\sigma^i_{Trend,T}} * \; SR^i_{Trend,t}$$

Therefore, the average Sharpe ratio measured across all assets *i* and time horizons *t* in *T* is:

[16] We apply a weighted least squares panel regression. Specifically, the relative weights for asset *i* in year *t* are the volatility of excess returns to trend following in that asset, normalized by the sum of full-sample volatilities for all assets in the trend-following strategy:

$$w^i_t = \frac{\sigma^i_{Trend,t}}{N^i_T \sum_j \sigma^j_{Trend,T}} \; for\ all\ assets\ i = 1, \ldots, M$$

This weighting ensures that single-period Sharpe ratios estimated from this model are consistent with realized multi-period Sharpe ratios, when aggregated across multi-period time horizons.

$$\langle SR_{Trend,T}\rangle = \sum_i \left(x^i * SR^i_{Trend,T}\right)$$

$$= \sum_i \left(\frac{\sigma^i_{Trend,T}}{\sum_j \sigma^j_{Trend,T}} * SR^i_{Trend,T}\right)$$

$$= \sum_i \left(\frac{\sigma^i_{Trend,T}}{\sum_j \sigma^j_{Trend,T}} * \left(\frac{1}{N^i_T}\sum_t \frac{\sigma^i_{Trend,t}}{\sigma^i_{Trend,T}} * \ SR^i_{Trend,t}\right)\right)$$

$$= \sum_i \frac{1}{N^i_T}\sum_t \left(\frac{\sigma^i_{Trend,t}}{\sum_j \sigma^j_{Trend,T}} * SR^i_{Trend,t}\right)$$

$$= \sum_i \frac{1}{N^i_T}\sum_t \left(\frac{\sigma^i_{Trend,t}}{\sum_j \sigma^j_{Trend,T}} * \left(\hat{\alpha}_T + \hat{\beta}_T |SR^i_t| + \varepsilon^i_t\right)\right)$$

$$for\ all\ i, j = 1, \dots, M\ and\ all\ t\ in\ T$$

Given a set of model coefficients $\hat{\alpha}_T$ and $\hat{\beta}_T$ and market moves SR^i_t, the portfolio-level Sharpe ratio is then:

$$SR^P_{Trend,T} = \ D_T \sum_i \frac{1}{N^i_T}\sum_t \left(\frac{\sigma^i_{Trend,t}}{\sum_j \sigma^j_{Trend,T}} \left(\hat{\alpha}_T + \hat{\beta}_T |SR^i_t| + \varepsilon^i_t\right)\right) for\ all\ i, j = 1, \dots, M\ and\ all\ t\ in\ T$$

$$SR^P_{Trend,T} = D_T \times (\alpha_T + \beta_T \langle |SR| \rangle_T)$$

where $\langle |SR| \rangle_T$is defined as the weighted average individual market move $|SR^i_t|$, weighted by $\frac{\frac{\sigma^i_{Trend,t}}{N^i_T}}{\sum_{t\prime}\sum_j \frac{\sigma^j_{Trend,t\prime}}{N^j_T}}$ over a period T, $\alpha_T = \ \hat{\alpha}_T \frac{\sum_t \sum_i \frac{\sigma^i_{Trend,t}}{N^i_T}}{\sum_j \sigma^j_{Trend,T}}$, and $\beta_T = \ \hat{\beta}_T \frac{\sum_t \sum_i \frac{\sigma^i_{Trend,t}}{N^i_T}}{\sum_j \sigma^j_{Trend,T}}$. The last equality follows because the weights of the regression are proportional to the realized volatility of trend following in asset *i* in year *t*, so $\sum_t \sum_i \frac{\sigma^i_{Trend,t}}{N^i_T} \varepsilon^i_t = 0$.

The trend efficacy parameters α_T and β_T are comparable across two time periods *T* and *T'* if *T* and *T'* share the number of years. This is because the magnitude of the ratios ${}^{\alpha_T}/_{\hat{\alpha}_T}$ and ${}^{\beta_T}/_{\hat{\beta}_T}$ are identical in expectation, assuming a stationary volatility process. The ratios average 0.896 over all rolling decades in the full sample from 1880 to present.

Using the above model, we can estimate the impact *I* of each component on risk-adjusted portfolio performance $SR^P_{Trend,T}$ in any sub-period *T* relative to the full sample average $\overline{SR^P_{Trend,T}}$. In our construction of full sample averages, we consider all rolling periods of $N_T = 10$ years. For example:

$$\overline{\alpha_T} = \frac{1}{N_{decades}} \sum_{T' \in decades}^{N_{decades}} \alpha_{T'}$$

We can therefore write the impact decomposition as:

$$\overline{SR^P_{Trend,T}} - SR^P_{Trend,T} = I_{moves} + I_{efficacy} + I_{diversification}$$

where

$$I_{moves} = D_T \times \left(\alpha_T + \beta_T \overline{\langle |SR| \rangle_T}\right) - SR^P_{Trend,T}$$

$$I_{efficacy} = D_T \times \left(\overline{\alpha_T} + \overline{\beta_T}\ \overline{\langle |SR| \rangle_T}\right) - I_{moves} - SR^P_{Trend,T}$$

$$I_{diversification} = \overline{D_T \times (\alpha_T + \beta_T \langle |SR| \rangle_T)} - I_{moves} - I_{efficacy} - SR^P_{Trend,T}$$

$$= \overline{SR^P_{Trend,T}} - I_{moves} - I_{efficacy} - SR^P_{Trend,T}$$

Note that the order of the decomposition matters. We evaluate the economic impact of diversification last as that is the only factor that applies at the portfolio, rather than the asset, level. In this paper we focus on results that first evaluate the impact of the magnitude of market moves, and then evaluate the impact of trend efficacy. For robustness we also considered the reverse ordering. Although the exact quantification differs slightly, results are consistent under either approach.

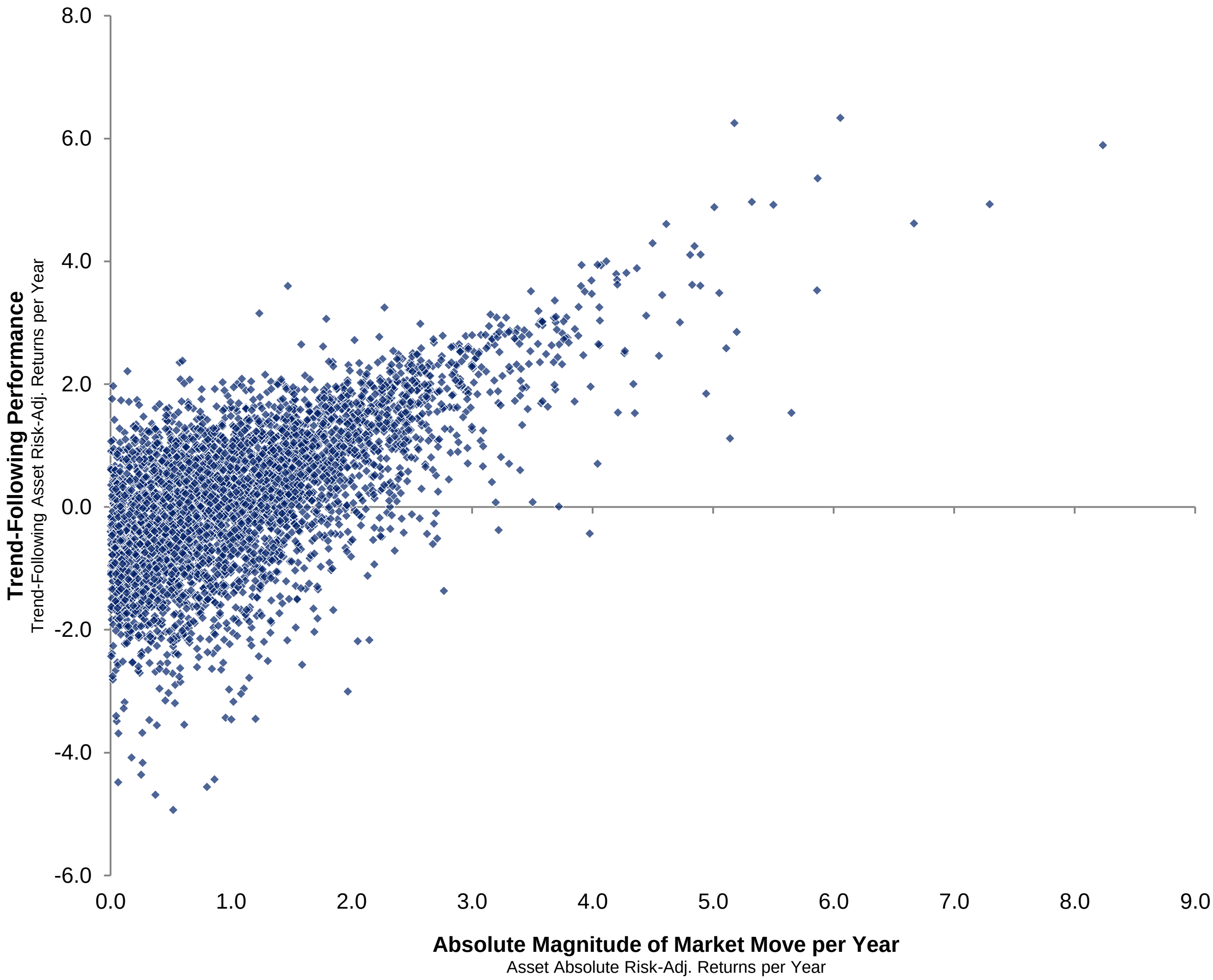
Disclaimer

AQR Capital Management is a global investment management firm and may or may not apply investment techniques or methods of analysis similar to those described herein. The views expressed here are those of the authors and not necessarily those of AQR.

Exhibit 1: Full data sample

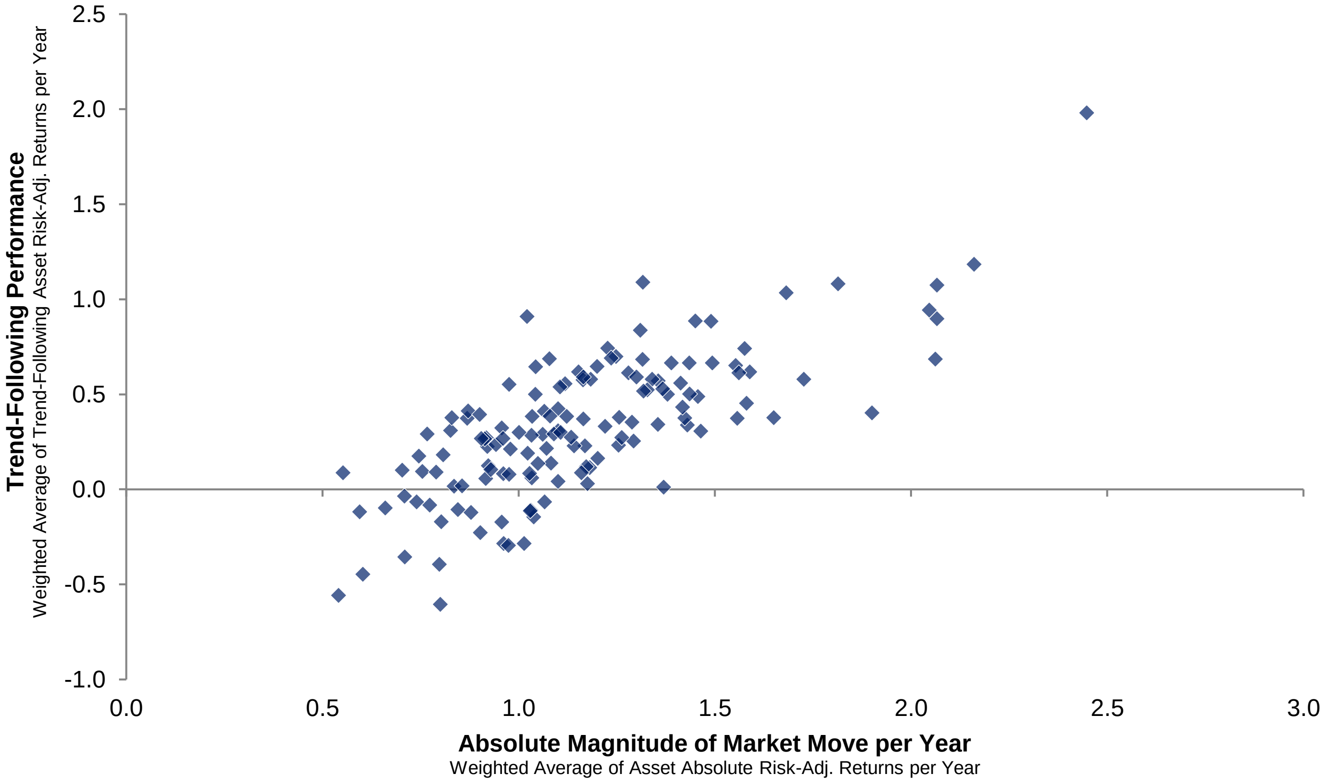
Hypothetical Trend-Following Performance vs. Magnitude of Market Moves per Asset per Year

January 1, 1880 – December 31, 2018



Source: AQR. For each asset in each year, the absolute risk-adjusted return is calculated as the absolute value of the annual excess return divided by the realized volatility of the asset in that year. The 3-Month T-Bill is the risk-free rate used to derive the risk-adjusted returns. This analysis is provided for illustrative purposes only and is not based on an actual portfolio AQR manages. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers.

Exhibit 2: Full data sample, weighted average by year
Hypothetical Trend-Following Performance vs. Magnitude of Market Moves per Year
January 1, 1880 – December 31, 2018

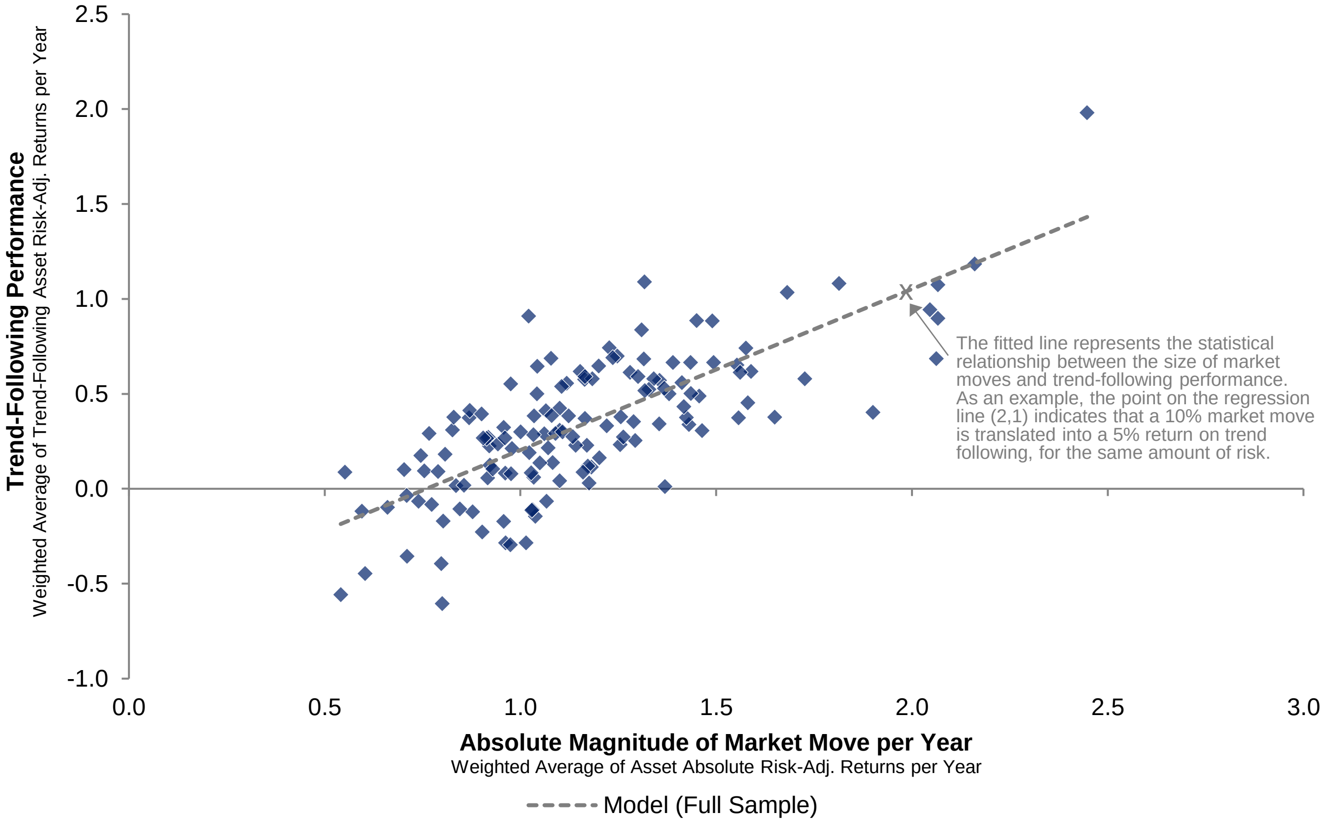


Source: AQR. For each asset in each year, the absolute risk-adjusted return is calculated as the absolute value of the annual excess return divided by the realized volatility of the asset in that year. Risk-adjusted returns shown above represent the weighted average for each calendar year. Risk-adjusted returns are weighted by the trend-following risk taken in each market in each year. The 3-Month T-Bill is the risk-free rate used to derive the risk-adjusted returns. This analysis is provided for illustrative purposes only and is not based on an actual portfolio AQR manages. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers.

Exhibit 3: Trend following benefits in part from larger market moves

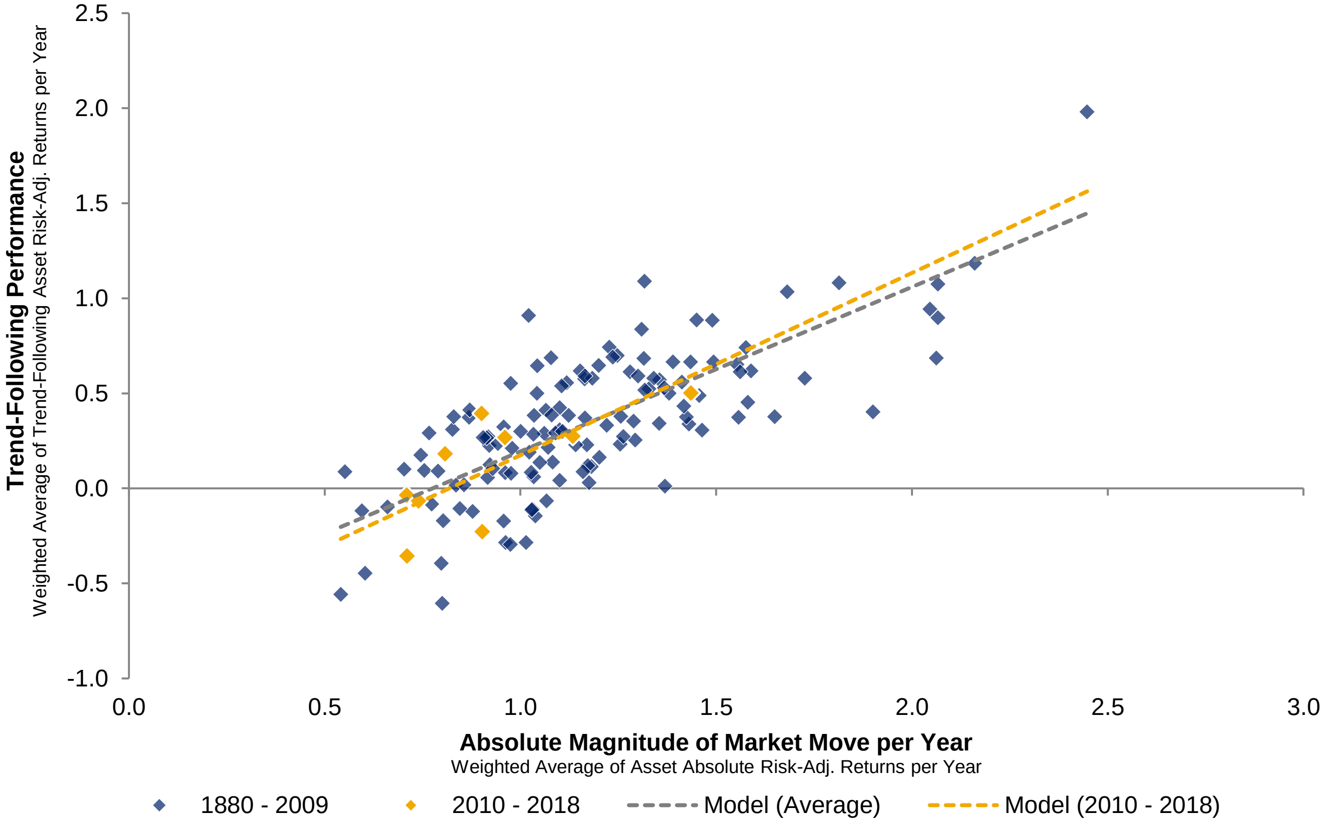
Hypothetical Trend-Following Performance vs. Magnitude of Market Moves per Year

January 1, 1880 – December 31, 2018



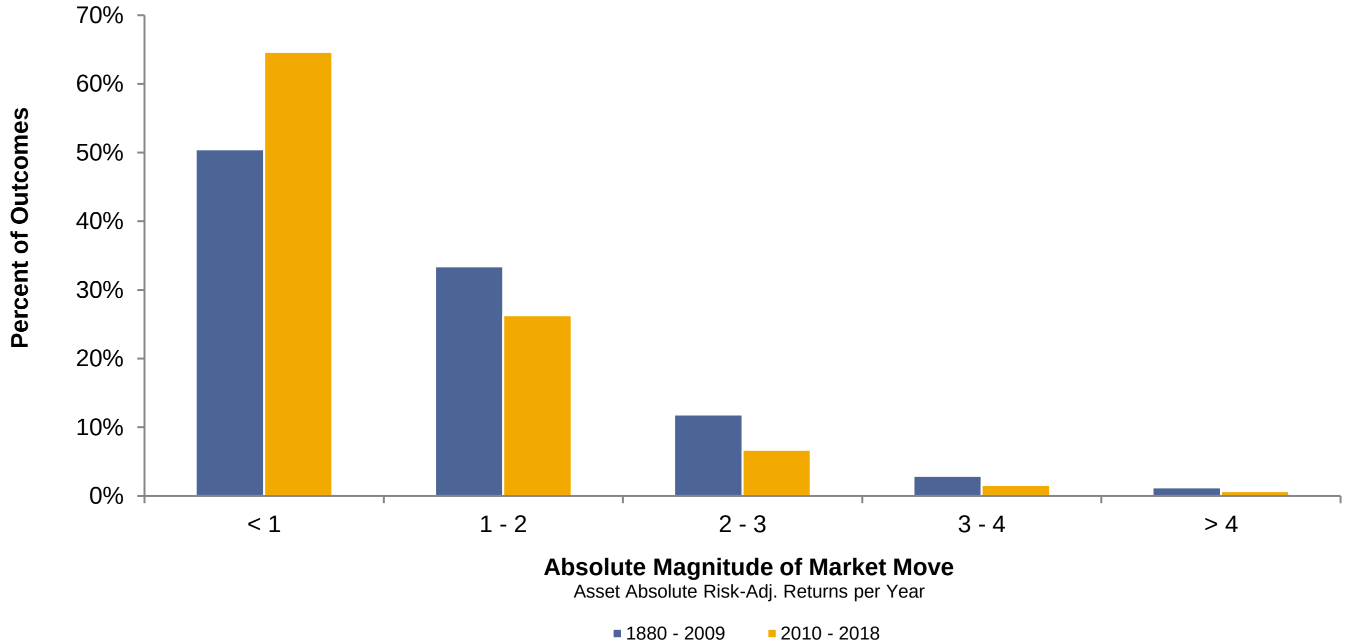
Source: AQR. For each asset in each year, the absolute risk-adjusted return is calculated as the absolute value of the annual excess return divided by the realized volatility of the asset in that year. Risk-adjusted returns shown above represent the weighted average for each calendar year. Risk-adjusted returns are weighted by the trend-following risk taken in each market in each year. The 3-Month T-Bill is the risk-free rate used to derive the risk-adjusted returns. This analysis is provided for illustrative purposes only and is not based on an actual portfolio AQR manages. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers.

Exhibit 4: Large market moves have been scarce in recent years
Hypothetical Trend-Following Performance vs. Magnitude of Market Moves per Year
January 1, 1880 – December 31, 2018



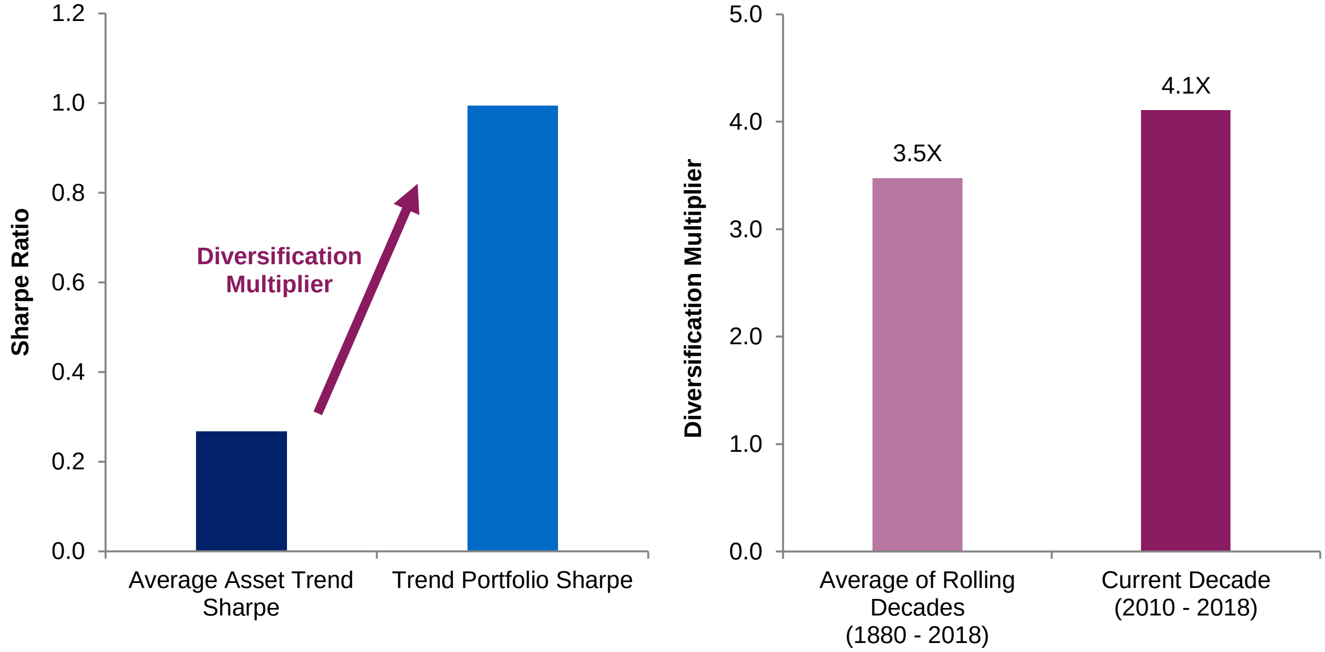
Source: AQR. For each asset in each year, the absolute risk-adjusted return is calculated as the absolute value of the annual excess return divided by the realized volatility of the asset in that year. Risk-adjusted returns shown above represent the weighted average for each calendar year. Risk-adjusted returns are weighted by the trend-following risk taken in each market in each year. The 3-Month T-Bill is the risk-free rate used to derive the risk-adjusted returns. This analysis is provided for illustrative purposes only and is not based on an actual portfolio AQR manages. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers.

Exhibit 5: Smaller market moves have been more prevalent in recent years
Empirical Distribution of Magnitude of Market Moves
January 1, 1880 – December 31, 2018



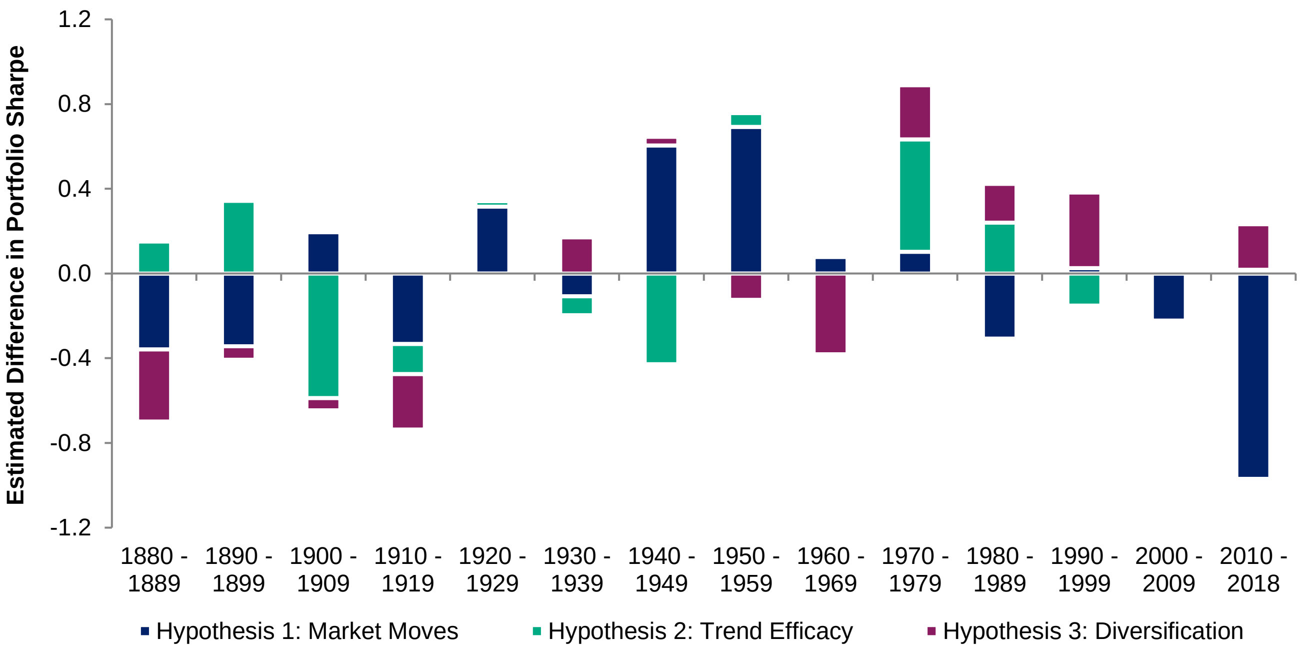
Source: AQR. For each asset in each year, the absolute risk-adjusted return is calculated as the absolute value of the annual excess return divided by the realized volatility of the asset in that year. The 3-Month T-Bill is the risk-free rate used to derive the risk-adjusted return. The empirical distribution of outcomes shown above is derived by calculating the percentage of observations that fall into the categories specified. There are 3,841 observations from 1880 – 2009, and 563 from 2010 – 2018. For illustrative purposes only. Past performance is not a guarantee of future performance.

Exhibit 6: Trend-following performance depends on diversification
Quantifying Diversification by Time Period
January 1, 1880 – December 31, 2018



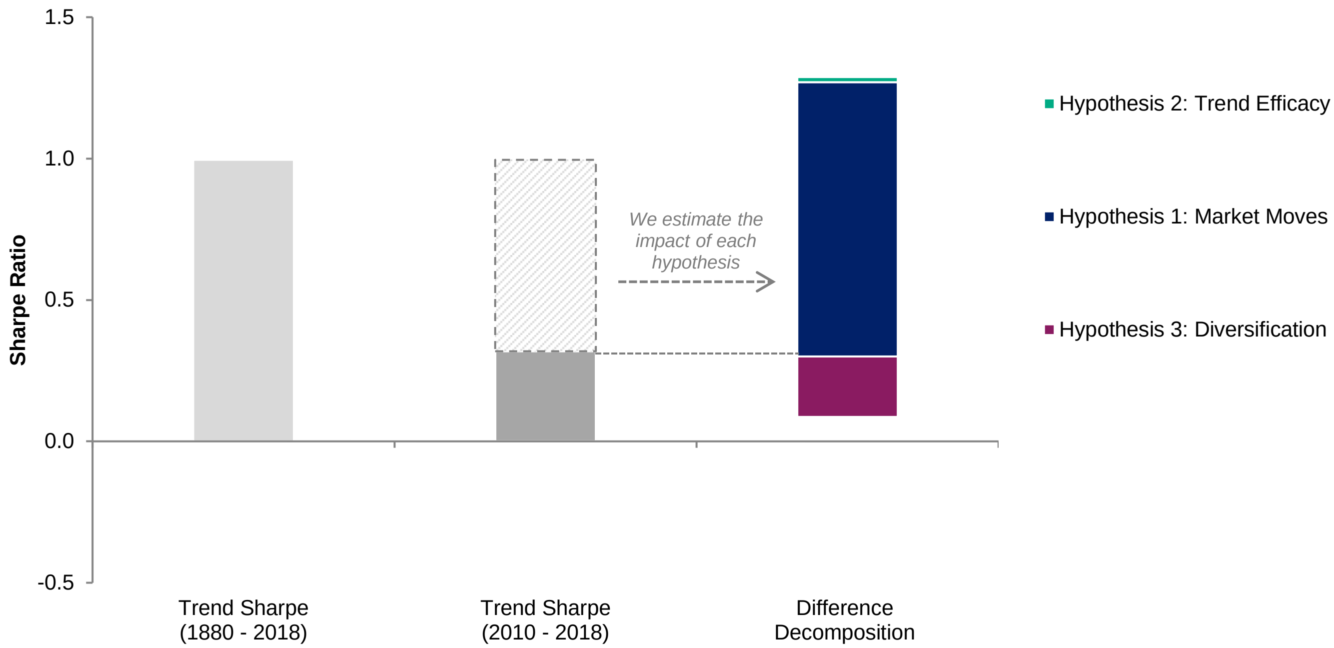
Source: AQR. The average asset trend Sharpe is the weighted average Sharpe ratio from trend following on each asset in the strategy. Asset Sharpe ratios are weighted by the trend-following risk taken in each market. The 3-Month T-Bill is the risk-free rate used to derive the Sharpe ratio. This analysis is provided for illustrative purposes only and is not based on an actual portfolio AQR currently manages. Diversification does not eliminate the risk of experiencing investment losses. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers.

Exhibit 7: Drivers of trend-following performance by decade
Attribution of Difference in Hypothetical Trend-Following Sharpe Ratios by Decade
January 1, 1880 – December 31, 2018



Source: AQR. The 3-Month T-Bill is the risk-free rate used to derive the Sharpe ratio. The Sharpe ratios are based on the hypothetical trend-following strategy backtest, net of estimated transaction costs and gross of fees. Differences in Sharpe ratios are estimated by incrementally changing one aspect of the model. Difference in Sharpe due to market moves is calculated from the difference in the Sharpe ratio for the specific decade shown versus the implied Sharpe ratio from utilizing market moves over the full sample. Difference in Sharpe ratio due to trend efficiency is measured based on the implied incremental change in Sharpe ratio from utilizing model coefficients that correspond to the full sample model. Difference in Sharpe ratio due to diversification is measured based on the implied incremental change in Sharpe ratio from utilizing the full sample diversification multiplier. Diversification does not eliminate the risk of experiencing investment losses. The chart above is a hypothetical illustration and not representative of an actual investment. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. For illustrative purposes only and not representative of any portfolio that AQR currently manages. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers. Please read important disclosures in the Disclaimers.

Exhibit 8: Smaller market moves are the primary driver of recent trend performance
Attribution of Difference in Hypothetical Trend-Following Sharpe Ratios
January 1, 1880 – December 31, 2018



Source: AQR. The 3-Month T-Bill is the risk-free rate used to derive the Sharpe ratio. The Sharpe ratios are based on the hypothetical trend-following strategy backtest, net of estimated transaction costs and gross of fees. Differences in Sharpe ratios are estimated by incrementally changing one aspect of the model. Difference in Sharpe due to market moves is calculated from the difference in the Sharpe ratio for the specific decade shown versus the implied Sharpe ratio from utilizing market moves over the full sample. Difference in Sharpe ratio due to trend efficiency is measured based on the implied incremental change in Sharpe ratio from utilizing model coefficients that correspond to the full sample model. Difference in Sharpe ratio due to diversification is measured based on the implied incremental change in Sharpe ratio from utilizing the full sample diversification multiplier. Diversification does not eliminate the risk of experiencing investment losses. The chart above is a hypothetical illustration and not representative of an actual investment. Please read performance disclosures in the Disclaimers for a description of the investment universe and the allocation methodology used to construct the trend-following strategy. For illustrative purposes only and not representative of any portfolio that AQR currently manages. Hypothetical data has inherent limitations, some of which are disclosed in the Disclaimers. Please read important disclosures in the Disclaimers.