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Protecting the Downside of Trend When It Is Not Your Friend

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PanAgora Asset Management is a quantitative investment manager whose proprietary approach is designed to capitalize on inefficiencies across market cycles and to deliver relative and absolute returns through distinct and innovative equity, multi-asset and risk premia strategies. PanAgora's approach combines the firm's fundamental investment philosophy and original research with an advanced quantitative framework. These elements come together in an open, collaborative environment that builds upon the intellectual versatility of its team and leverages their complementary strengths — essential to serving the evolving objectives of institutional investors worldwide.

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Dr. Qian has a distinguished career in investment management as well as academia. A renowned researcher, Dr. Qian's pioneering work, "On the Financial Interpretation of Risk Contribution: Risk Budgets Do Add up", became a cornerstone for what is commonly referred to as "Risk Parity" type investment strategies today. Dr. Qian's research has helped PanAgora become a leader in the area of risk budgeting strategies by launching the first Risk Parity Portfolios earlier this decade. He is the author of the recently published book, *Risk Parity Fundamentals*. Dr. Qian has authored many articles regarding quantitative equity investment techniques as well as co-author of the book, *Quantitative Equity Portfolio Management: Modern Techniques and Applications.*

Prior to joining PanAgora, Dr. Qian was a Portfolio Manager and part of the Asset Allocation team at 2100 Capital, an alternative investments firm. His prior experience includes a role as Senior Asset Allocation Analyst on Putnam Investments' Global Asset Allocation team. Before joining Putnam, he was a fixed-income Quantitative Analyst at Back Bay Advisors.

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PanAgora

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ABSTRACT: *Simple trend-following strategies have been documented as cost-effective, transparent alternatives to the hedge-fund style managed futures strategies. Although largely capturing the returns of the managed futures industry, those simple strategies may periodically suffer significant losses due to oversimplified trend signals and underdiversified portfolio construction. In this article, the authors show that trend-following strategies with moderate sophistication and better diversification can significantly reduce the downside risk of simple trend-following strategies without sacrificing much upside potential. The authors therefore recommend that investors who seek the benefits of cost-effective trend-following strategies consider adding reasonable complexity to the strategies.*

TOPICS: ***Real assets/alternative investments/private equity, futures and forward contracts, portfolio construction, risk management****

Trend-following strategies using exchange-traded futures and OTC currency forwards (hence, aka managed futures strategies[1]) have been widely pursued by commodity trading advisors (CTAs). These strategies typically buy assets with upward trends, and sell assets with downward trends, justified by the assumption that past changes in price can predict future changes in price. There are a number of explanations for the profitability of trend-following strategies, ranging from investors' behavioral biases to market friction. Despite ongoing theoretical debate, trend-following strategies have historically proven to deliver positive returns that, on average, are uncorrelated with equities and bonds. More importantly, they tend to provide downside protection during crisis periods (Moskowitz, Ooi, and Pedersen 2012; Greyserman and Kaminski 2014; and Hamill, Rattray, and Hemert 2016). This feature of long-term positive returns while also offering a strategic offset to crisis risk has attracted a steady flow of assets into trend-following strategies over time. According to Barclay-Hedge, total assets under management for the managed futures industry has steadily grown from around $10 billion in 1990 to around $369.5 billion as of 2018 Q2.

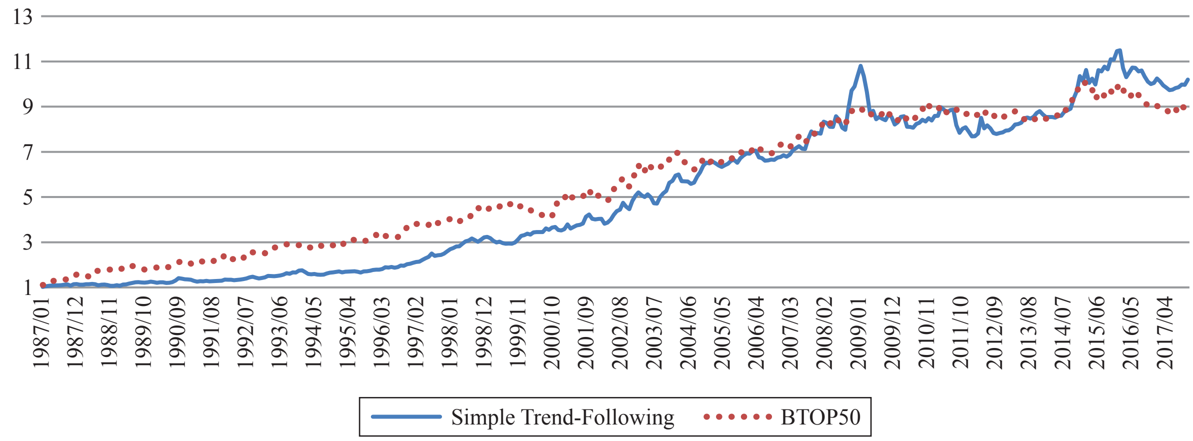
Traditionally, managed futures strategies have been classified as hedge funds, and typically lacked transparency and cost-effectiveness. Recently, research has shown that the performance of the managed futures industry can be explained by simple, systematic trading rules. For example, Hurst, Ooi,

[1] Although trend-following and managed futures are often used side by side in the literature, managed futures, in principle, may refer to any type of strategies that are implemented with liquid futures and forwards. Nonetheless, we use trend-following and managed futures interchangeably in this article.

*All articles are now categorized by topics and subtopics. **View at IPRJournals.com.**

Exhibit 1

Cumulative Returns of Trend-Following Strategies



Notes: The simple trend-following strategy is based on the 12-month return sign rule and the equal volatility portfolio construction. The BTOP50 Index is a trend-following index constructed by BarclayHedge to represent the managed futures industry performance.

and Pedersen (2013) showed that the sign of an asset's past (1-, 3-, and 12-month) return positively predicts its future direction. They formed trend-following portfolios consisting of long positions in assets with positive past return signs, and short positions in assets with negative past return signs. Each position was sized to have the same ex ante volatility to have comparable influence in the portfolio (hereafter the equal volatility portfolio). These portfolios largely explained the performance of the managed futures industry, as evidenced by their high correlations and large R^2 with the managed futures indexes. Therefore, investors seeking the benefits of managed futures may consider transparent, cost-efficient trend-following approaches instead of high-fee, black-box hedge funds.

Although the same return for a lower fee and greater transparency is appealing, there can be limitations of being overly simplistic. For example, simple trend-following strategies may suffer larger and longer drawdowns compared to a more complex strategy. Exhibit 1 shows the cumulative return of a simulated equal-volatility portfolio in which the direction of the trend is based on the sign of an asset's 12-month trailing return, and the size of the position is inversely proportional to its historical volatility. Simulation details will be discussed in the main text. As a reference, it also shows the performance of the BTOP50 Index, which is constructed by BarclayHedge and captures the performance of the largest managed futures funds. For an equal-foot comparison, the performance of the simple trend-following strategy is scaled to have a similar volatility as the BTOP50 Index (around 10% per annum over 1987–2017). Consistent with the findings of Hurst, Ooi, and Pedersen (2013), the simulated simple trend strategy has performed well (net of cost Sharpe ratio = 0.8) and captured a significant portion of the index performance (monthly correlation = 0.44); however, the simple trend strategy suffered deep losses over prolonged periods with a large maximum drawdown (–26% over February 2009–February 2012) and a long time to recover (43 months). Similar (or worse) results are found for trend strategies in which the signal is derived from the sign of an asset's one-month and three-month trailing return. Hurst, Ooi, and Pedersen (2017) also reported comparable drawdown statistics of simple trend-following rules over a period of more than 100 years (1880–2016).

The periodic losses from trend-following strategies are unavoidable, especially when multiple markets exhibit simultaneous reversals; however, the magnitude and duration of losses from simple trend rules could be substantially reduced. On the one hand, the simple rule based on the sign of an asset's trailing return always holds a position in a market, even when the underlying market exhibits no significant trends. This introduces the possibility of entering positions based on noise rather than any evidence of strong, trending behavior. In addition, this simple rule tends to be slow-moving and may hold on to a losing position for too long. Finally, the equal

EXHIBIT 2
Data Coverage

Commodities			Equity Indexes	Sovereign Bonds	Currencies	
Soybean Oil	Brent Crude	Copper	Australian SPI 200	US 2-Year	AUD	BRL
Corn	WTI Crude	Aluminum	Canadian TSX 60	US 5-Year	CAD	CLP
Soybean Meal	Heating Oil	Nickel	German DAX	US 10-Year	CHF	CZK
Soybean	Gas Oil	Zinc	Spain IBEX 35	US 30-Year	EUR	HUF
Wheat	Natural Gas	Gold	France CAC 40	German 2-Year	GBP	KRW
Cocoa	Gasoline	Silver	UK FTSE 100	German 5-Year	JPY	MXN
Cotton			Hong Kong Hang Seng	German 10-Year	NOK	PLN
Coffee			Italy MIB	German 30-Year	NZD	RUB
Sugar			Japan TOPIX	Australian 10-Year	SEK	TRY
Lean Hogs			Netherlands Amsterdam IDX	Canadian 10-Year		ZAR
Live Cattle			Sweden OMX 30	UK 10-Year		
			Singapore Index			
			US S&P 500			

Note: Data are sourced from the Commodity Research Bureau (CRB), Bloomberg, and DataStream.

volatility approach ignores the correlation of trends and likely concentrates risk in highly correlated trends. Failing to recognize and account for the correlation across trending assets can result in a significant drawdown when correlated trends simultaneously reverse.

In this article, we seek to enhance the simple trend-following strategies by improving both the trend signal definition and the portfolio construction process. First, we overlay a channel breakout entry/exit rule on the simple rule based on the sign of an asset's trailing return (hereafter the complex trend). We show that the complex trend improves the return distribution of the simple trend via better downside protection. Second, we apply a risk parity approach in the portfolio construction process, taking into account both the volatility and correlation structure of trends across multiple markets. We show that the risk parity approach improves upon the equal volatility approach via better diversification, which leads to more robust performance over time.

The rest of the article is organized as follows. Sections 2 and 3 describe data and methodology, respectively. Section 4 discusses the empirical results. We make concluding remarks in Section 5.

DATA

Our data consist of 60+ liquid futures/forwards contracts across asset classes and the world: 23 commodity futures, 13 equity index futures, 11 sovereign bond futures, and 19 developed and emerging markets currency (FX) forwards. Exhibit 2 lists the instruments by asset class. Specifically, daily futures prices are collected from the Commodity Research Bureau (CRB) and Bloomberg, whereas daily FX spot prices and local short-term interest rates are collected from DataStream and Bloomberg. Daily futures returns are calculated assuming contracts are rolled to the next nearest contract on the first day of the expiration month. For financial futures (equity index and sovereign bond futures), we backfill the history using derived returns from cash instruments.[2] Daily FX forward returns are calculated as FX spot returns adjusted for carry. We construct a price index for each instrument by compounding daily returns, from which we can calculate returns and trend signals over different horizons.

Appendix A (included in the online supplement) reports summary statistics of monthly returns for all instruments by commodity sector/asset class. Monthly futures returns are available as early as August 1959 (primarily agriculture commodities). Monthly FX

[2] Specifically, we backfill the equity index futures returns with the (gross dividends, excess cash) returns of the underlying indexes. We backfill the US Treasury futures returns with the derived returns from zero-coupon constant maturity yields of comparable duration. We find that the real and derived returns for the equity indexes and US Treasury futures are almost identical in the overlapping periods (perfect monthly correlations and close to 100% R^2).

EXHIBIT 3
Average Volatilities, Sharpe Ratios, and Pairwise Correlations by Asset Class

			Pairwise Correlation	
Asset Class	Ann. Volatility	Sharpe Ratio	Within Asset Class	With Other Asset Class
Commodities	31%	0.15	0.18	0.09
Equity Indexes	20%	0.29	0.61	0.09
Sovereign Bonds	6%	0.63	0.65	–0.09
Currencies	12%	–0.04	0.45	0.14

Note: The statistics are calculated based on monthly returns over the sample period August 1959–December 2017.

forwards returns begin in February 1973, when major currencies adopted the floating exchange rate regime. The complete coverage of all instruments begins in 2003. Exhibit 3 reports the average volatilities, Sharpe ratios, and pairwise correlations by asset class. Consistent with the findings in the literature, equities and sovereign bonds tend to yield long-term positive returns across countries (average Sharpe ratios are 0.29 and 0.63, respectively), whereas commodities and currencies may add or detract value over time (average Sharpe ratios are 0.15 and −0.04, respectively). In addition, asset volatilities are dramatically different across asset classes. Commodities, on average, exhibit the highest annual volatility (31%), followed by equity indexes (20%) and currencies (12%). The volatility of sovereign bonds (6%) has been about one-fifth that of commodities. Exhibit 3 also shows evidence of high correlations within the same asset class, and low/negative correlations across asset classes.

METHODOLOGY

Trend Signal

For illustration purposes, we construct a simple trend signal using the sign of the past 12-month return (hereafter the 12-month rule). Specifically, we hold a long (short) position in an asset if its past 12-month return is positive (negative). The 12-month rule has been a conventional method studied in the academic literature. Despite its simplicity, the 12-month rule is found to have good efficacy with a long-term Sharpe ratio between 0.5 and 1.0 across different asset classes (Moskowitz, Ooi, and Pedersen 2012; Baltas and Kosowski 2015; Kolanovic and Wei 2015).

Though simple and effective, the 12-month rule has two potential pitfalls. First, it always places a bet on an asset, even if there is no obvious trend in the underlying market. Hypothetically, if the S&P 500 equity index returned 0.01% over the past 12 months, the rule would require a long position in the index. The likely consequence is unnecessary costs associated with keeping an open position purely driven by noise. Second, the 12-month rule reacts slowly to trend reversals and may incur significant losses before it switches sign.

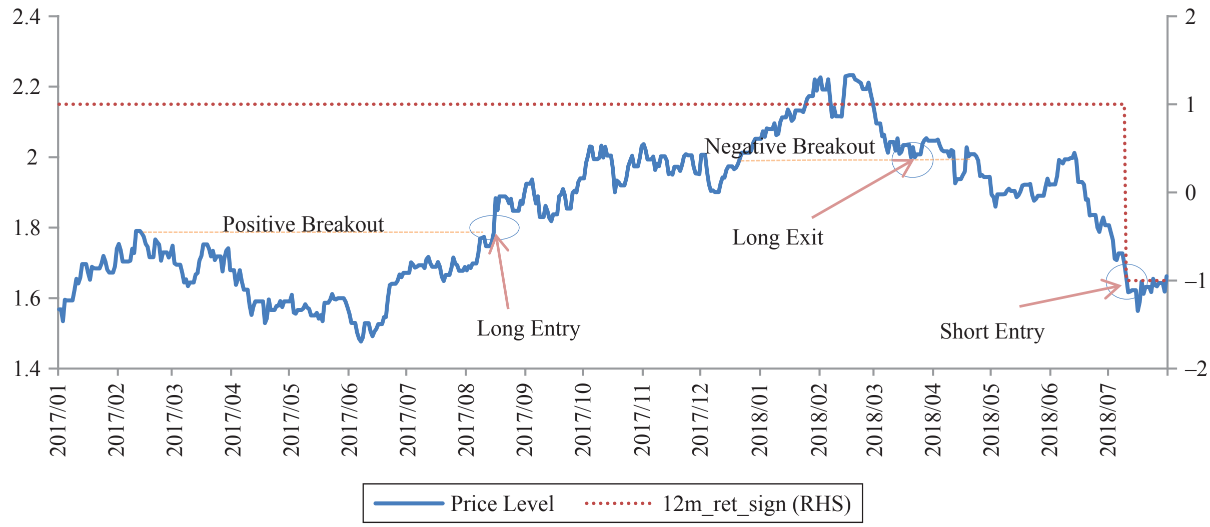
To enhance the simple trend signal, we incorporate a channel breakout entry/exit rule[3] as a filter on the original signal derived from the sign of the trailing 12-month return. Specifically, we enter a long (short) position in an asset only if both its past 12-month return is positive (negative) and the latest price has traded above (below) its recent n-day maximum (minimum). We exit a long (short) position if the latest price trades below (above) its recent n/2-day minimum (maximum), or the 12-month trailing return turns negative (positive). For illustration purposes, we set n = 200. The results are qualitatively similar for other parameters such as 150 and 100. The breakout rule is a popular technique used by practitioners and is found to be useful in distinguishing noise from actual trends, as well as stopping losses during trend reversals (Clenow 2013; Greyserman and Kaminski 2014).

Exhibit 4 provides a graphical example comparing the simple and complex trend signals, based on the futures prices for zinc from January 2016 to July 2018. The trend signal starts in January 2017 to allow for a

[3] Another way to enhance the 12-month rule is to mix it with similar signals over multiple horizons, such as the signs of the trailing 3-month and 1-month returns (Hurst, Ooi, and Pedersen 2013). The caveat to this mixed frequency return rule is that these signals are, in general, highly correlated due to similar construction and overlapping horizons. As a result, the mixed signal is under-diversified and tends to overweight short-horizon (one-month) trends. We will explore this aspect in another study.

EXHIBIT 4

Complex Trend Signal: Zinc, January 2017–July 2018



12-month learning window. As seen from the exhibit, the simple trend indicator ("12m_ret_sign") was always on, taking a value of 1 (long zinc) from January 1, 2017, to July 9, 2018, and switching to −1 (short zinc) from July 10, 2018. The complex trend indicator, on the other hand, was not on until the price broke above its trailing 200-day maximum on August 16, 2017 (positive 200-day breakout). It entered a long zinc position on that day and exited it on March 20, 2018, when the price dropped below its trailing 100-day minimum (negative 100-day breakout). It entered a short zinc position on July 10, 2018, when both the sign of zinc's 12-month trailing return turned negative and the price dropped below its past 200-day minimum.

Exhibit 4 shows that, compared to the simple trend signal, the complex trend signal has: (1) fewer open positions; and (2) higher turnover. Whereas (1) implies lower rollover costs, (2) implies higher rebalancing costs. In the example, the breakout exit helped lock in the gains, whereas the simple rule almost gave up all the gains. This was due to the fact that the reversal of zinc's bullish trend was persistent. In the case of a temporary retracement during a long-term trend, the complex trend may falsely exit and underperform against the simple trend. In other words, the added complexity may provide downside protection during trend reversals, but sacrifice upside participation during trend retracements. We will analyze the impact of transaction costs, as well as the trade-off between downside protection and upside participation, in the empirical section.

Portfolio Construction

In the previous section, we compare two signals used to determine security selection. In this section, we compare two portfolio construction approaches used to determine security weighting: the equal volatility approach and the risk parity approach.

The equal volatility (EV)[4] approach is a popular method to form a multiasset trend-following portfolio (Moskowitz, Ooi, and Pedersen 2012; Clenow 2013; and Hurst, Ooi, and Pedersen 2017). The essence of this approach is to size trending assets such that each position targets the same ex ante risk. Mathematically, for a trending asset i at time t,

$$w_t^i = trend_t^i \frac{vol_{target}}{N_t \times vol_t^i} \tag{1}$$

where $trend_t^i$ is an indicator function based on the trend signal (1 for upward trend, −1 for downward trend), vol_{target} is a prespecified annualized volatility target for individual positions, vol_t^i is the annual volatility of asset i

[4] Equal volatility is also known as inverse volatility, volatility parity, and naive risk parity.

at time t, and N_t is the number of trending assets (open positions) at time t. Easily proven, each position in the portfolio has an ex ante annualized volatility $\frac{vol_{target}}{N_t}$.

The EV approach accounts for volatility differences across assets in its security weighting. It allocates more weight to trending assets with low volatility (sovereign bonds and currencies), and less weight to trending assets with high volatility (commodities and equities). This prevents high volatility trends from dominating the portfolio risk. It, however, does not take into account the correlations among trending assets. Failure to account for correlation results in two problems. The first problem is the inability to accurately target a constant level of portfolio risk. For a portfolio of 20 trending assets with a volatility target of 10% per annum, the equal volatility approach could size each position to target 0.5% risk. Position volatility is only additive in a portfolio context if all pairwise correlation across all 20 assets is 1. As a result, the equal volatility portfolio will likely deliver volatility well below its volatility target. To account for this, most equal volatility approaches will set a volatility target used to size positions to be much higher than their desired volatility target at the total portfolio level (Moskowitz, Ooi, and Pedersen 2012). This scalar is derived from an assumption of average correlation across trends over time. In practice, the ex ante risk of the portfolio will be time varying around this average. Perversely, in periods in which the trends are highly correlated, the portfolio will be taking above-average risk, and in periods in which the trends are spread out and diversifying to one another, the portfolio will be taking below-average risk. This leads to the second problem of ignoring correlation. If the majority of trending positions are highly correlated, the portfolio risk will be concentrated in these highly correlated trends, making the portfolio vulnerable to a sharp reversal in a singular market theme.

The risk parity (RP) approach has become a popular portfolio construction method in long-only asset allocation strategies due to its diversification optimality in absence of any active view of the market (Qian 2006). The essence of this approach is to solve for weights that equalize the total risk contribution of each position to the portfolio, taking into account both the volatility and correlation structure. The approach can be easily extended to long–short trend-following strategies as follows.

Specifically, we first specify the trend indicator vector at time t,

$$I_t = \left.\begin{bmatrix} trend_t^1 \\ trend_t^2 \\ \vdots \\ trend_t^{N_t} \end{bmatrix}\right\} N_t \times 1 \tag{2}$$

where $trend_t^i$ and N_t are defined in Equation (1).

We denote the asset covariance matrix at time t,

$$\Sigma_t = \left.\begin{bmatrix} var_t^1 & cov_t^{1,2} & \cdots & cov_t^{1,N_t} \\ cov_t^{1,2} & var_t^2 & \cdots & cov_t^{2,N_t} \\ \vdots & \vdots & \ddots & \vdots \\ cov_t^{1,N_t} & cov_t^{2,N_t} & \cdots & var_t^{N_t} \end{bmatrix}\right\} N_t \times N_t \tag{3}$$

where var_t^i is the variance of asset i, and $cov_t^{i,j}$ is the covariance between asset i and j at time t.

The trend-adjusted covariance matrix is then calculated as

$$\Sigma_t^{adj} = (I_t \times I_t') \odot \Sigma_t \tag{4}$$

where I_t' is the transposed vector of trend indicators, and $\odot$ denotes elementwise multiplication. In the trend-adjusted covariance matrix, the variances of each asset will remain the same as in the original asset covariance matrix, but the covariances among assets will adapt to whether an asset is in an upward or downward trend. For example, suppose the covariance between the S&P 500 and WTI crude oil at time t is positive. Furthermore, assume that according to a specified trend signal, the S&P 500 is in an upward trend while WTI crude oil is in a downward trend. In this scenario, the trend-adjusted covariance between the S&P 500 and WTI crude oil is adjusted to be negative in recognition that we are holding a long position in one asset, but a short position in the other.

Finally, we apply a numerical algorithm with the trend-adjusted covariance matrix Σ_t^{adj} to solve for the RP weights of each trend, subject to a prespecified volatility target for the portfolio and a nonnegativity constraint for the weights. The final asset weights will be the trend weights multiplied by the trend sign (thus allowing both long and short). The technical details of

EXHIBIT 5
Performance Summary

	Equal Volatility Portfolio		Risk Parity Portfolio	
	Simple Trend	Complex Trend	Simple Trend	Complex Trend
Annual Excess Return	10.94%	11.47%	13.42%	13.31%
Annual Rollover Costs	1.24%	0.94%	1.69%	1.18%
Annual Rebalancing Costs	1.19%	1.96%	2.49%	2.50%
Annual Excess Return Net Costs	8.51%	8.57%	9.23%	9.62%
Annual Standard Deviation	10.00%	10.00%	10.00%	10.00%
Sharpe Ratio	0.85	0.86	0.92	0.96
Annual Downside Deviation	6.13%	5.86%	5.70%	5.68%
Sortino Ratio	1.39	1.46	1.62	1.69
Max Drawdown (MaxDD)	–25.67%	–18.89%	–19.47%	–18.39%
Annual Net Ret. over MaxDD	0.33	0.45	0.47	0.52
Peak-to-Trough Period	2009.2–2012.2	1980.2–1980.7	1980.2–1981.4	1980.2–1980.7
Trough-to-Recovery Length (Months)	43	23	32	24
Leverage	238%	183%	312%	222%
Annual One-Way Turnover	281%	499%	647%	657%
Avg. Positions per Month	45	27	45	27

Notes: The leverages of 2-, 5-, and 30-year bond futures are expressed in the 10-year equivalent. Sample period: 1961–2017.

solving the RP weights are not the focus of this article. Interested readers are referred to Maillard, Roncalli, and Teiletche (2010) and Chaves et al. (2012).

EMPIRICAL RESULTS

We compare four trend-following portfolios. We consider portfolios that select securities using both simple and complex trend signals, and weight securities using both equal volatility and risk parity portfolio construction approaches. Each portfolio is rebalanced monthly, based on the month-end trend signals and covariance matrix estimates. The asset covariance matrix in Equation (3) is estimated using monthly returns based on an expanding window with exponential decay.[5] Since the number of available assets increased over time, we allow for a one-year learning period before including a new asset into the portfolio. For the EV portfolios, we set the volatility target for *each individual position* at 40% per annum, following Moskowitz, Ooi, and Pedersen (2012). For the RP portfolios, we set the volatility target for *the portfolio* at 10% per annum. These volatility targets are used to solve initial weights. They are not essential in comparing final results, as all portfolios will be adjusted to have the same ex post volatilities.

Transaction costs (rollover and rebalancing costs) are incorporated in our empirical evaluation, as explained in Appendix B (included in the online supplement). In addition, we also account for implementation slippage by allowing for a one-day trading lag. Even though transaction costs of liquid futures/forwards are modest, their impact on the relative performance between the four portfolios is nontrivial, as these portfolios have significantly different leverage and turnover.

Performance Summary

Exhibit 5 compares key characteristics of the four portfolios over the entire period of 1961–2017. The results for 2003–2017 (during which all instruments became available) are similar and available upon request. For an equal foot comparison, all portfolios are scaled to have an ex post annual volatility of 10% over 1961–2017.

Compared to the simple trend portfolios, the complex trend portfolios have fewer holdings and lower leverage (for both the EV and RP approach). This is expected since the breakout entry and exit filter embedded in the complex trend signal creates a higher

[5] Results are robust to different decay rates, such as one-, two-, and five-year half-life. The results reported in this article are based on a two-year half-life decay rate.

standard for establishing and maintaining positions. As a result, the complex trend portfolios incur lower rollover costs. On the other hand, the complex trend portfolios have higher turnover and rebalancing costs due to more frequent signal changes. Net of transaction costs, the complex trend portfolios yield only marginally better Sharpe ratios (0.86 vs. 0.85 for the EV approach, and 0.96 vs. 0.92 for the RP approach). The modest improvement in Sharpe ratios is only part of the story. The downside risk measures for the complex trend portfolios are considerably lower than those of the simple trend portfolios, as seen from the lower downside deviations and the maximum drawdowns (MaxDDs), as well as a shorter trough-to-recovery length. As shown in Exhibit 5, the downside risk-adjusted ratios (Sortino ratios and return over MaxDD ratios) are all higher for the complex trend portfolios compared to the simple trend portfolios.

Compared to the EV portfolios, the RP portfolios have higher leverage and turnover (for both the simple and complex trend). The higher leverage is due to the fact that negatively correlated trends are typically levered more significantly in an RP portfolio in order to balance risk contribution across positions. The higher turnover is due to the time-varying dynamics of the trend correlation structure. Whereas an EV portfolio rebalances in response to changes in volatility, an RP portfolio rebalances in response to changes in both volatility and correlation. As a result, the RP portfolios have higher rollover costs due to greater total leverage, and rebalancing costs due to changing correlations. Net of transaction costs, however, the RP portfolios still outperform the EV portfolios in almost all dimensions, such as higher Sharpe ratios, Sortino ratios, and return over MaxDD ratios, as shown in Exhibit 5. This suggests that the RP approach not only enhances the mean return, but also improves the return distribution via better downside protection.

Upside Participation and Downside Protection

To further understand the return–risk tradeoff among different portfolios, we look at two additional characteristics: the upside and downside participation ratios. As rigorously defined in Qian (2015), the upside (downside) participation ratio measures the percentage of the benchmark return that is captured by a studied portfolio when the benchmark performance is positive (negative). Specifically, we use r_i and r_b to denote the net return of portfolio i and the benchmark portfolio; the upside participation ratio of portfolio i is $\frac{E(r_i|r_b>0)}{E(r_b|r_b>0)}$, where $E(\ )$ denotes expectation or average, and "|" denotes "conditional on." Similarly, the downside participation ratio is $\frac{E(r_i|r_b<0)}{E(r_b|r_b<0)}$. The difference between the upside and downside participation ratio is referred to as *participation advantage*. A positive participation advantage suggests that the studied portfolio captures more of the benchmark's upside than its downside.

We use the simple trend EV portfolio as the benchmark, and report the participation ratio statistics of the other portfolios in Exhibit 6. The results serve as strong evidence that the complex trend EV portfolio offers decent upside participation (90%) and downside protection (79%) to the simple trend EV portfolio, resulting in a positive participation advantage of 11%. The RP approach, on the other hand, outperforms the EV approach from the perspectives of both upside (101%) and downside participation (94%), with a positive participation advantage of 7%. Combined together, the complex trend RP portfolio has an even better participation advantage (18%) relative to the benchmark.

We further look at the upside participation and downside protection during extreme periods. Exhibit 7 reports the cumulative returns (excess cash, net of transaction costs) of different portfolios during the top five and bottom five performance periods for the simple trend EV portfolio (benchmark). As seen from Panel A, when the benchmark portfolio performed extremely well (mean cumulative return = 34.89%), the other portfolios captured about 84% to 86% of the upside. On the other hand, when the benchmark portfolio suffered significant losses (mean cumulative loss = −17.38%), the losses of other portfolios were generally more moderate, capturing only 38% to 70% of the downside. More strikingly, during the maximum drawdown period of the benchmark portfolio (September 2009 to February 2012), the complex signal actually produced a moderately positive return.

To sum it up, adding both complexity to the signal definition and risk parity as the portfolio construction methodology improves the performance of a simple trend-following strategy. Although the breakout entry/exit rule may not improve the Sharpe ratio, it provides downside protection and improves the return distribution of the simple 12-month rule. The RP construction, on the other hand, consistently adds value to the EV construction via improving both its upside and downside capture. We investigate in the next section the driver behind the outperformance of risk parity.

Exhibit 6
Upside and Downside Participation

	Equal Volatility Portfolio		Risk Parity Portfolio	
	Simple Trend (benchmark)	Complex Trend	Simple Trend	Complex Trend
Positive Benchmark Performance: 423 Months				
Mean Ex. Ret. Net of Costs	2.33%	2.09%	2.36%	2.20%
Upside Participation Ratio		90%	101%	94%
Negative Benchmark Performance: 266 Months				
Mean Ex. Ret. Net of Costs	–1.89%	–1.49%	–1.77%	–1.44%
Downside Participation Ratio		79%	94%	76%
Participation Advantage		11%	7%	18%

Note: Sample period: 1961–2017.

Exhibit 7
Upside Participation and Downside Protection

	Equal Volatility Portfolio		Risk Parity Portfolio	
Period	Simple Trend (benchmark)	Complex Trend	Simple Trend	Complex Trend
Panel A: Upside Participation during the Best Performance Periods of Simple Trend				
2008.9–2009.2	30.76%	33.03%	15.57%	23.55%
2003.8–2004.3	23.66%	16.82%	25.81%	19.17%
2002.3–2003.2	31.35%	25.66%	28.61%	24.33%
2012.2–2016.2	42.63%	32.98%	36.66%	36.76%
2004.7–2008.6	46.05%	38.15%	43.27%	45.16%
Mean Cum. Ret.	34.89%	29.33%	29.99%	29.79%
Upside Participation		84%	86%	84%
Panel B: Downside Protection during the Worst Performance Periods of Simple Trend				
2009.2–2012.2	–25.67%	0.91%	–3.14%	8.15%
1961.2–1961.11	–16.92%	–12.68%	–15.62%	–11.58%
1980.2–1980.7	–15.72%	–18.89%	–15.76%	–18.39%
1966.8–1967.2	–15.05%	–6.20%	–12.08%	–4.67%
2016.2–2017.6	–13.55%	–3.53%	–14.49%	–6.25%
Mean Cum. Losses	–17.38%	–8.08%	–12.22%	–6.55%
Downside Participation		46%	70%	38%

Notes: The percentage numbers with two decimal places are the cumulative returns (excess cash, net of transaction costs) of each portfolio in the specified periods. The upside (downside) participation is the mean cumulative returns ratio (relative to the benchmark). To identify the best and worst performance periods, we first identify the 20 largest drawdown periods of the simple trend portfolio. The best performance periods are the top five trough-to-peak periods, as ranked by annualized returns. The worst performance periods are the five largest drawdown (peak-to-trough) periods. Sample period: 1961–2017.

Diversification Benefit from Risk Parity

Compared to the EV approach, the RP approach, in principle, should yield a more diversified portfolio by taking correlations among trends into account. To investigate the diversification benefits from the RP approach, we conduct the following grouping analysis. The analysis is based on the simple trend rule, and similar results are available upon request for the complex trend rule.

At each month-end, we sort the trending assets into three (evenly divided) groups based on their average pairwise trend correlations. Exhibit 8 provides a snapshot

EXHIBIT 8

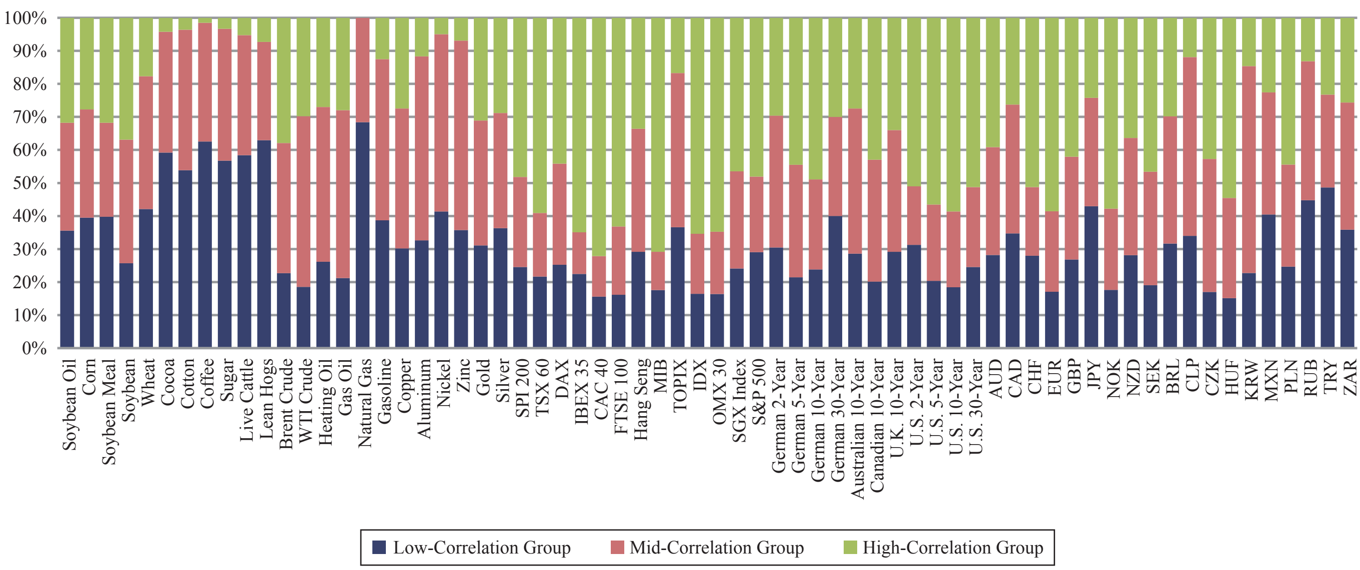
Trends Sorted by Average Pairwise Correlations, December 31, 2017

Low-Correlation Group		Mid-Correlation Group		High-Correlation Group	
Asset Trend	**Avg. Pairwise Corr.**	**Asset Trend**	**Avg. Pairwise Corr.**	**Asset Trend**	**Avg. Pairwise Corr.**
Bearish BRL	–0.16	Bearish Canadian 10-Year	0.03	Bullish CAD	0.20
Bearish TRY	–0.16	Bearish German 30-Year	0.03	Bullish NOK	0.20
Bearish Soybean Oil	–0.09	Bullish Live Cattle	0.05	Bullish S&P 500	0.20
Bearish Cocoa	–0.07	Bullish CHF	0.07	Bullish AUD	0.21
Bullish German 2-Year	–0.06	Bullish Cotton	0.08	Bullish FTSE 100	0.21
…	…	…	…	…	…

Notes: The trend signal is based on the 12-month return sign as of December 31, 2017. The pairwise correlations are calculated as trend-sign adjusted asset correlations.

EXHIBIT 9

Frequency in Low-, Mid-, and High-Correlation Trend Groups

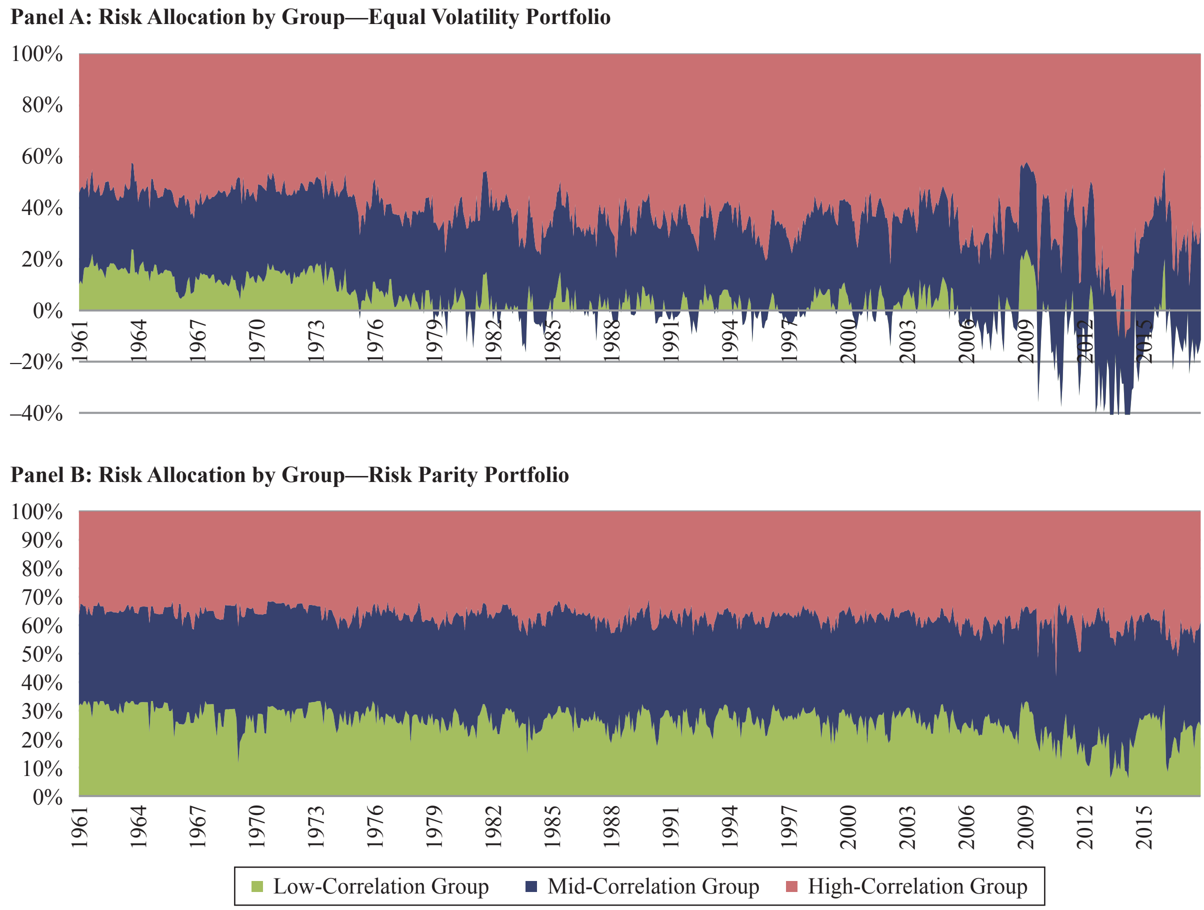


Notes: The trend signal is based on the 12-month return sign. Sample period: 1961–2017.

of the sorted groups as of December 31, 2017. To save space, only five trending assets in each group are listed. As shown in Exhibit 8, the simple trend rule indicated bullish trends in global equities as well as commodity currencies, and bearish trends in some emerging market currencies as well as agricultural commodities. The bullish trends in global equities and commodity currencies were sorted into the high-correlation trend group due to their high average pairwise correlations (0.2) with other identified trends. On the other hand, the bearish trends of BRL, TRY, soybean oil, and cocoa, and the bullish trend in the German two-year bond, were sorted into the low-correlation trend group.

The above example shows that trend correlations are different from asset correlations. For example, even though BRL and AUD tend to be positively correlated, their trends are negatively correlated if the two assets are trending in opposite directions. Since an asset trend changes direction over time, it can be sorted into the low-, mid-, or high-correlation group depending on the then-trending dynamics in the market. Exhibit 9 plots the frequency of each asset being in the low-, mid-,

EXHIBIT 10
Risk Allocation by Group



Notes: The trend signal is based on the 12-month return sign. Sample period: 1961–2017.

or high-correlation group over the entire sample. In general, agricultural commodities are more likely sorted into the low-correlation group. For example, cocoa, coffee, sugar, and hogs have about a 60% chance of being in the low-correlation group, versus a lower than 10% chance of being in the high-correlation group. On the other hand, global equities are often sorted into the high-correlation group. For example, France CAC40 and Italy MIB have about a 70% chance of being in the high-correlation group, and a lower than 20% chance of being in the low-correlation group. Note that some fixed income trends (for example, US Treasury bonds) have a higher than 50% chance of being in the high-correlation group. This suggests that although fixed income assets are generally diversifying in long-only asset allocation portfolios, they are not necessarily so in a long–short trend-following portfolio.

Exhibit 10 shows the time-varying risk contribution of each group in the EV portfolio and the RP portfolio. The risk contribution of each group is the sum of the risk contribution of individual trends within the group. We use the capital allocations (both long and short) and the estimated asset covariance matrix to calculate the risk contribution of individual trends. As shown in Panel A, the risk allocation of the EV portfolio is very unbalanced across the groups, with the high-correlation group being the dominant risk contributor. The low-correlation group tends to have limited (or negative) risk contribution to the total portfolio. The overconcentration in high-correlation trends was particularly severe in the post-GFC "risk-on, risk-off" period (2009–2014). The RP portfolio, on the other hand, has a more balanced risk allocation across the groups.

EXHIBIT 11
Summary Statistics by Group

	Equal Volatility Portfolio			Risk Parity Portfolio		
	Low-Corr. Group	Mid-Corr. Group	High-Corr. Group	Low-Corr. Group	Mid-Corr. Group	High-Corr. Group
Pairwise Corr.	–0.02	0.05	0.11	–0.02	0.05	0.11
Risk Contr.	2%	36%	62%	26%	37%	37%
Return Contr.	20%	33%	46%	27%	36%	38%
Sharpe Ratio	0.63	0.75	0.73	0.55	0.80	0.85
Monthly Return Correlations						
Low-Corr. Group	1.00	–0.08	–0.04	1.00	–0.21	–0.17
Mid-Corr. Group		1.00	0.38		1.00	0.35
High-Corr. Group			1.00			1.00

Notes: The trend signal is based on the 12-month return sign. The pairwise correlations are calculated as trend-sign adjusted asset correlations. Sample period: 1961–2017.

Exhibit 11 reports summary statistics by group for each portfolio from 1961 to 2017. On average, the pairwise correlation for the low-, mid-, and high-correlation groups is –0.02, 0.05, and 0.11. The EV portfolio's total risk is dominated by the high correlation group, whereas the RP portfolio's total risk is more balanced across the groups. The return contributions share a similar pattern. In the EV portfolio, the most diversifying asset trends accounted for only 20% of the portfolio's total return. In contrast, the RP portfolio's return was much more balanced across all the trending assets. Clearly, the RP portfolio has a more balanced risk and return contribution from each group.

A diversified portfolio among groups does not necessarily lead to superior performance. For example, if the low-correlation trend group has inferior performance against the other groups, it is actually desirable to allocate lower risk to the low-correlation group. As shown in Exhibit 11, however, the Sharpe ratios are comparable among the low-, mid-, and high-correlation groups. Furthermore, the returns of the low-correlation group, in general, are negatively correlated with the returns of the other two groups. Both the Sharpe ratio and return correlation statistics justify the diversification benefit of the low-correlation trend groups, and hence explain the optimality of the RP approach relative to the EV approach.

CONCLUSION

Simple trend-following strategies (based on the sign of an asset's trailing return and the equal volatility construction) have been documented as cost-effective, transparent alternatives to the hedge-fund-style managed futures strategies. Although largely capturing the returns of the managed futures industry, those simple strategies may periodically suffer significant losses due to oversimplified trend signals and underdiversified portfolio construction.

In this article, we show that a trend-following strategy with moderate sophistication (a combination of the sign of past return with a breakout entry/exit filter) and better diversification (the risk parity portfolio construction approach) can significantly reduce the downside risk of simple trend-following strategies. The complex trend rule improves the return distribution of the simple trend rule via favorable upside participation and downside protection. The risk parity approach, on the other hand, improves the strategy performance via more balanced risk and return contributions from trending markets. We therefore recommend investors who seek the benefits of simple trend-following strategies to consider adding reasonable complexity into their strategies.

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