ReSolve
ASSET MANAGEMENT

PEERING AROUND CORNERS:

HOW TO REPLICATE TREND-FOLLOWING MANAGED FUTURES

Whitepaper

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ABSTRACT

Trend-following managed futures can be an excellent complement to traditional stocks and bonds. This paper explores the construction of a strategy to replicate the returns to a popular managed futures index. By using a replicating strategy that captures the broad exposures to equities, fixed income, commodities, and currencies that are present in the index while also identifying the underlying strategies used by trend-following managed futures funds, the authors produce a replication strategy that accurately captures the performance and character of the category. The replication strategy exceeds a 0.85 correlation with the benchmark index, suggesting that the representative models span most of the models used in the index. Investors who can access the Replication strategy at lower fees than the average managed futures fund may experience stronger net returns due to fee alpha.

PEERING AROUND CORNERS: HOW TO REPLICATE TREND-FOLLOWING MANAGED FUTURES

In finance, it is common to explain the returns of a market, fund, or index using other securities, markets, funds, factors, and so on. This type of modeling serves several potential purposes. The Capital Asset Pricing Model (CAPM) aimed to explain the returns of an equity portfolio by finding the portfolio's sensitivity to the market portfolio. Fama and French's groundbreaking paper, "The Cross Section of Expected Stock Returns," attempted to improve on the CAPM by introducing factors related to firm size and book-to-market (value). Returns Based Style Analysis (RBSA) is still the predominant method used to determine how much of an investment manager's returns can be accounted for by common benchmarks or risk factors.

Returns Based Style Analysis (RBSA) regression produces weights of explanatory factors that, when held in a portfolio, would track the return of the target strategy. If the selected factors effectively explain the target strategy, the tracking portfolio should closely follow the target strategy's path. Any returns exceeding what the tracking portfolio would be anticipated to produce are considered alpha. For example, Frazzini, Kabiller, and Pedersen (2013)[1] found that Warren Buffett's historical returns in excess of the returns to the S&P 500 could be explained by his use of cheap, safe, high-quality stocks combined with consistent leverage. The pursuit of alpha is the ultimate goal of active management, and many investors dedicate their entire careers to it.

REPLICATING HEDGE FUND RETURNS

There are some investors who are not interested in alpha, or who feel they do not possess the skills or access to find consistent alpha. They may believe that while markets are not perfectly efficient, many inefficiencies can be explained by well-defined risks and other effects that can be harvested using simple rules. In the past, these inefficiencies powered the alpha of active mutual funds and hedge funds.

However, academics and practitioners have since demystified these sources of return and have begun offering exposure to them through public indices at much lower fees. As a result, products that capture these inefficiencies are now available to investors as alternative betas, rather than as sources of alpha for active managers. Smart beta products that seek exposure to value, momentum, quality, low volatility, or size effects are examples of these quasi-passive strategies.

Some hedge fund strategies use securities and techniques that are not well-suited to investment structures that are accessible to all investors. However, regulatory frameworks can evolve over time, such that strategies that were once impossible to democratize may become feasible down the road. Competitive market forces provide powerful incentives for managers to offer these strategies at scale.

TREND-FOLLOWING MANAGED FUTURES

Trend-following managed futures is a hedge-fund strategy that involves trading futures contracts in various financial markets, such as commodities, currencies, and stock and bond indices, with the aim of identifying and capitalizing on trends in these markets. This strategy has its roots in the dawn of liquid futures markets in the 1970s and a number of the firms that trade in this style have been around for decades, with well established track records.

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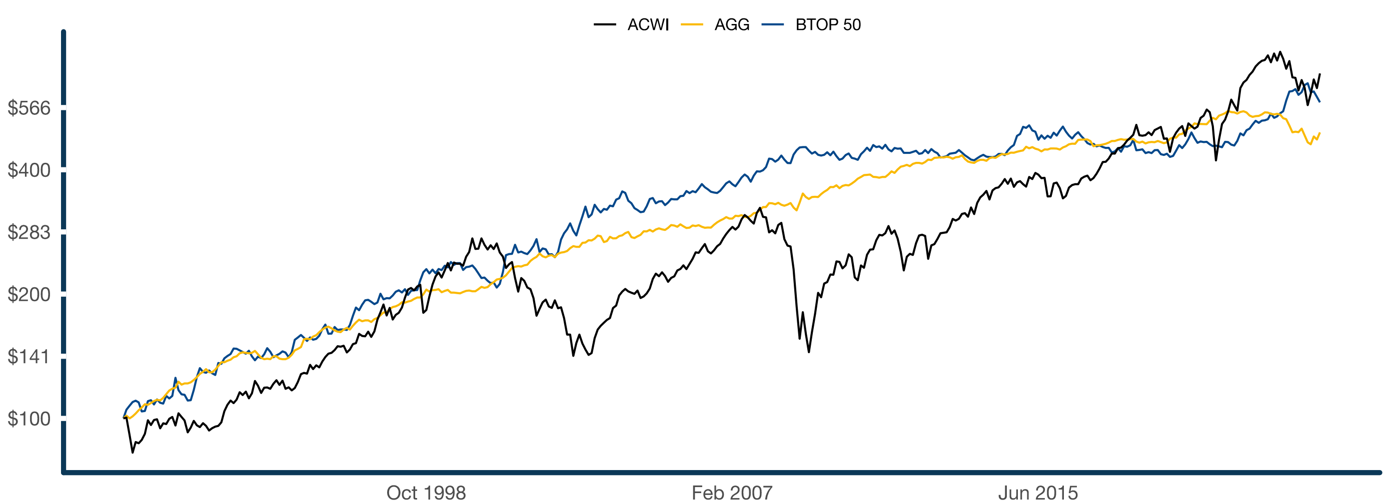
[1] Frazzini, A., Kabiller, D., & Pedersen, L. H. (2013). Buffett's Alpha. Financial Analysts Journal, 69(4), 29-43.
https://www.tandfonline.com/doi/abs/10.2469/faj.v69.n4.1

Several factors may explain the persistence of returns to trend-following strategies across several decades. For instance, while information propagates at an ever-faster rate over time, market complexity also increases. As a result, it takes some time for investors to reach a consensus on the expected direction of markets[2]. As investors move to add or withdraw capital from markets, this triggers a change in price that takes time to evolve[3]. There is also research to suggest that investors underreact to changes in market conditions near turning points, and then overreact to large price moves, pushing prices far beyond fundamentals[4].

Markets have historically produced persistent trends that managed futures strategies can profit from. Because trend-following strategies can trade both long and short across many markets, they have historically produced returns with low correlation to major stock and bond benchmarks, making them an excellent diversifying strategy for traditional portfolios. Figure 1 and Tables 1 and 2 describe the cumulative total return, performance statistics, and pairwise correlations between the MSCI All-Cap World Index ("ACWI"), the Barclays Aggregate Bond Index ("AGG"), and the Barclay BTOP 50 Index from August 1, 1990, through January 31, 2023. The Barclay BTOP 50 Index is an investable index that seeks to replicate the overall composition of the managed futures industry with regard to trading style and overall market exposure. Barclay Hedge publishes monthly returns for the BTOP 50 Index back to January 1987.

Figure 1. Cumulative monthly total returns for MSCI All-Cap World Index, Barclays Aggregate Bond Index, and Barclay BTOP 50 Managed Futures Index, August 1st 1990 – January 31st 2023.



Source: Bloomberg. ACWI and AGG returns use ACWI and AGG ETF total returns from inception. Prior to inception on March 28, 2008 ACWI ETF returns are extended with MSCI ACWI USD Total Return Index (Net) with data from Bloomberg. Prior to inception on September 26, 2003 AGG ETF returns are extended with Bloomberg Aggregate Bond Index USD Total Returns with data from Bloomberg. BTOP 50 returns are sourced from Barclay Hedge. Past performance does not guarantee future results.

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[2] Bailey, D. H., & López de Prado, M. (2013). The economic case for time series data mining. Journal of Investment Strategies, 3(3), 23-34. https://doi.org/10.21314/JIS.2013.107

[3] Bouchaud, J.-P., Farmer, J. D., & Lillo, F. (2009). How markets slowly digest changes in supply and demand. In Handbook of Financial Markets: Dynamics and Evolution (pp. 57-156). North-Holland. https://arxiv.org/pdf/0809.0822

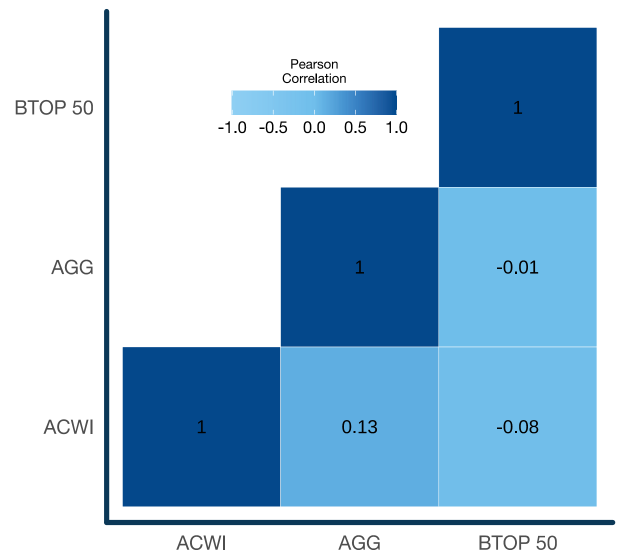
[4] Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. Journal of Finance, 61(4), 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Table 1. Monthly total return performance statistics for MSCI All-Cap World Index, Barclays Aggregate Bond Index, and Barclay BTOP 50 Managed Futures Index, August 1st, 1990 – January 31st, 2023.

	MSCI ACWI	BARCLAYS AGG	BARCLAY BTOP 50
Start Date	Aug 01, 1990	Aug 01, 1990	Aug 01, 1990
Annualized Return	6.08%	5.01%	5.56%
Sharpe Ratio	0.34	0.78	0.47
Annualized Volatility	16.10%	4.10%	8.60%
Max Drawdown	-55.30%	-17.00%	-16.10%

Source: Bloomberg. ACWI and AGG returns use ACWI and AGG ETF total returns from inception. Prior to inception on March 28, 2008 ACWI ETF returns are extended with MSCI ACWI USD Total Return Index (Net) with data from Bloomberg. Prior to inception on September 26, 2003 AGG ETF returns are extended with Bloomberg Aggregate Bond Index USD Total Returns with data from Bloomberg. BTOP 50 returns are sourced from Barclay Hedge. Past performance does not guarantee future results.

Table 2. Monthly return Pearson correlations for MSCI All-Cap World Index, Barclays Aggregate Bond Index, and Barclay BTOP 50 Managed Futures Index, August 1st, 1990 – January 31st, 2023.



Source: Bloomberg. ACWI and AGG returns use ACWI and AGG ETF total returns from inception. Prior to inception on March 28, 2008 ACWI ETF returns are extended with MSCI ACWI USD Total Return Index (Net) with data from Bloomberg. Prior to inception on September 26, 2003 AGG ETF returns are extended with Bloomberg Aggregate Bond Index USD Total Returns with data from Bloomberg. BTOP 50 returns are sourced from Barclay Hedge. Past performance does not guarantee future results.

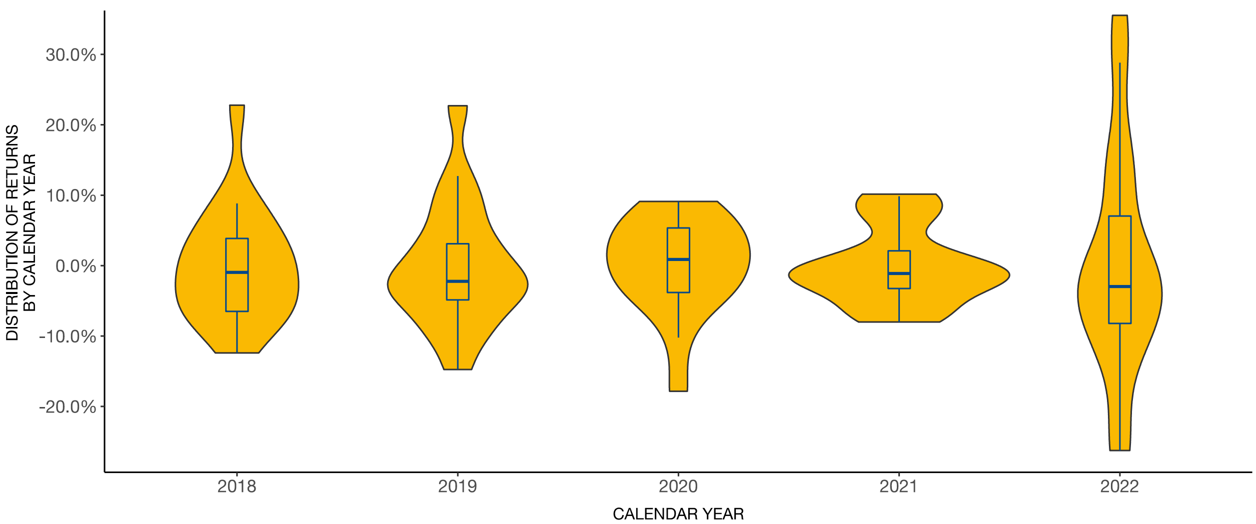
Note that the Barclay BTOP 50 Index, proxying the net performance of trend-following managed futures strategies, has produced returns that are competitive with stock and bond benchmarks over the past three decades, based on the information contained in Table 1. Monthly volatility is about twice that of bonds and half the volatility of stocks, and the BTOP 50 Index has exhibited a lower correlation to both stocks and bonds than we observe between stocks and bonds. As a result, managed futures are often considered an ideal complement to traditional portfolios.

DISPERSION IN TREND-FOLLOWING MANAGED FUTURES FUND RETURNS

On average, based on the low historical average correlations exhibited in Table 2, trend-following managed futures funds have historically been an attractive diversifier for traditional portfolios of stocks and bonds. However, while the Barclay BTOP Index and other common indices of trend-following funds are typically constituted with investable funds, few allocators will operationalize an allocation to all of the underlying managers.

Rather, most investors choose to allocate to just one fund or perhaps a small sample of funds. This may be problematic for those seeking category-like returns most years. That's because there is a great deal of variation in how funds express a trend-following strategy. Funds may choose different universes of markets to trade, utilize different trend lengths and definitions, apply different weighting schemes, use different risk management techniques and stop-losses, or include exposures to other systematic factors like carry. As a result, the returns to trend-following managed futures funds can exhibit large dispersion from year-to-year.

Figure 2. Total return dispersion by calendar year for a representative universe of public trend-following managed futures funds.



Source: Funds were selected from the Morningstar Systematic Trend category. Funds with less than five years of continuous data through January 2023 were excluded. Funds used (by ticker symbol) include ABYIX, ACXIX, AHLIX, AMFNX, AQMIX, CSAIX, EQCHX, EVOIX, GMSSX, LCSIX, LFMIX, LOTIX, MFTNX, PQTIX, QMHIX, RYIFX, SUPIX, WAVIX. Past performance does not guarantee future results.

The violin plot with box and whisker in Figure 2 illustrates how, in most years, returns to trend-following funds tend to cluster together with a few outliers. A violin plot is a type of graph that is used to show the distribution of a dataset and looks like a shape that is similar to a violin. The wide part of the shape shows where there are more data points, and the narrow part shows where there are fewer data points. The box and whisker chart inside the yellow violin plots summarize the distribution of returns each year by showing the median, quartiles, and range of the data, with whiskers at the top and bottom extending to 95th and 5th percentile values, respectively.

Over the five years from 2018 through 2022 the returns to individual trend-following managed futures funds[5] deviated from the average of all funds[5] by 9 percentage points about half the time. The 95 percent range of dispersion was almost 27 percentage points. This dispersion motivates a search for methods to gain exposure to the underlying theme of trend-following with minimal tracking error.

REPLICATING TREND-FOLLOWING MANAGED FUTURES

Replication strategies seek to deliver a return experience that closely tracks the return trajectory of a target benchmark. Which prompts the question: What is the most appropriate trend-following managed futures benchmark?

Strategy replication is at root a data science exercise. While it is critical to understand the underlying mechanics of the target index, the quality of any replication model will ultimately depend on the number of data points available to generate a good fit. While the BTOP 50 Index is representative of trend-following managed futures strategies, and publishes monthly returns back to the late 1980s, the index only started publishing daily returns data in 2010. This is not ideal for replication.

The SG Trend Index, managed by Société Générale, tracks the 10 largest (by AUM) trend-following managed futures funds, and is representative of the trend-follower niche in the managed futures space. The SG Trend Index is equally weighted, and rebalanced and reconstituted annually. And the index publishes daily returns back to January 1st, 2000.

To be included in the index, managers must meet the following criteria:

- Must be open to new investment
- Must report daily returns
- Must be an industry recognized trend-follower as determined at the discretion of the SG Index Committee
- Must exhibit significant correlation to trend-following peers and the SG Trend Indicator

In an ideal world, a replication strategy would have access to the actual holdings and trading in the funds that constitute the index. Quite naturally however, managers do not share their current positioning and trades with outside parties. As a result, replication strategies must infer the weighted average holdings of the managers that constitute the benchmark strictly from an understanding of the types of markets that managed futures funds typically trade, the kinds of strategies they typically employ, and reported index returns.

There are two general approaches to index replication. The first, which we'll label "top down" replication, involves using the returns over the past few days or weeks to solve for the underlying average holdings of managers in the index at each point in time. The latter, which we'll call "bottom-up" replication, seeks to uncover the underlying strategies that funds in the index are using to form portfolios. Once we uncover the weighting to a representative basket of underlying strategies, we can run the strategies forward to determine index level holdings at each point in time.

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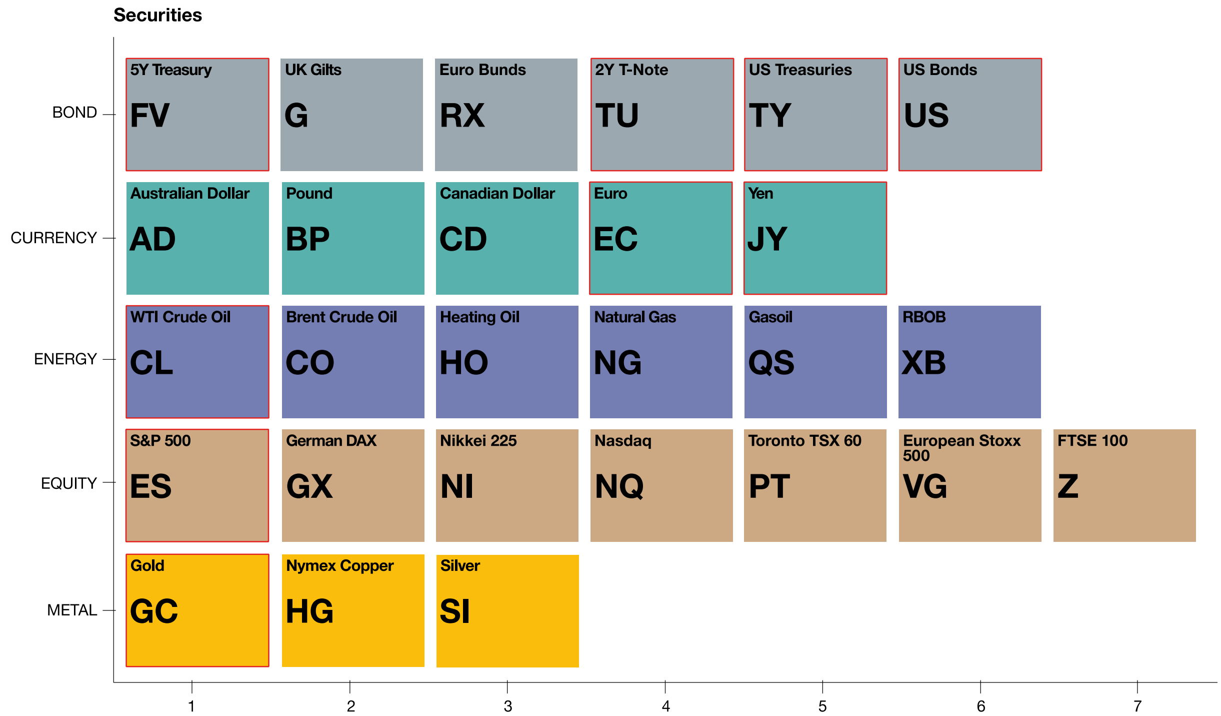
[5] Funds included in the analysis include ABYIX, ACXIX, AHLIX, AMFNX, AQMIX, CSAIX, EQCHX, EVOIX, GMSSX, LCSIX, LFMIX, LOTIX, MFTNX, PQTIX, QMHIX, RYIFX, SUPIX, WAVIX.

DATA

Daily returns of the Trend Index were downloaded from Société Générale Prime Services[6]. Futures market data is from CSI Data and Refinitiv. Futures total returns include price returns and roll returns but not collateral yield, so they represent excess returns above the borrowing rate.

Two investment universes were utilized for modeling purposes. The “medium” sized universe contains 27 liquid futures markets representing equity and bond indices, major currency crosses with the USD, along with energy and metal commodities. The “small” universe contains 9 liquid futures markets representing the same sectors.

Figure 3. Futures universe used for analysis. Small universe of markets highlighted in red.



Source: ReSolve Asset Management SEZC (Cayman) (“ReSolve Global”). For illustrative purposes only.

TOP-DOWN REPLICATION

If we were replicating Warren Buffett’s portfolio, the top-down approach would be akin to trying to identify the portfolio of stocks that best replicates his returns by regressing his track record on the universe of stocks.

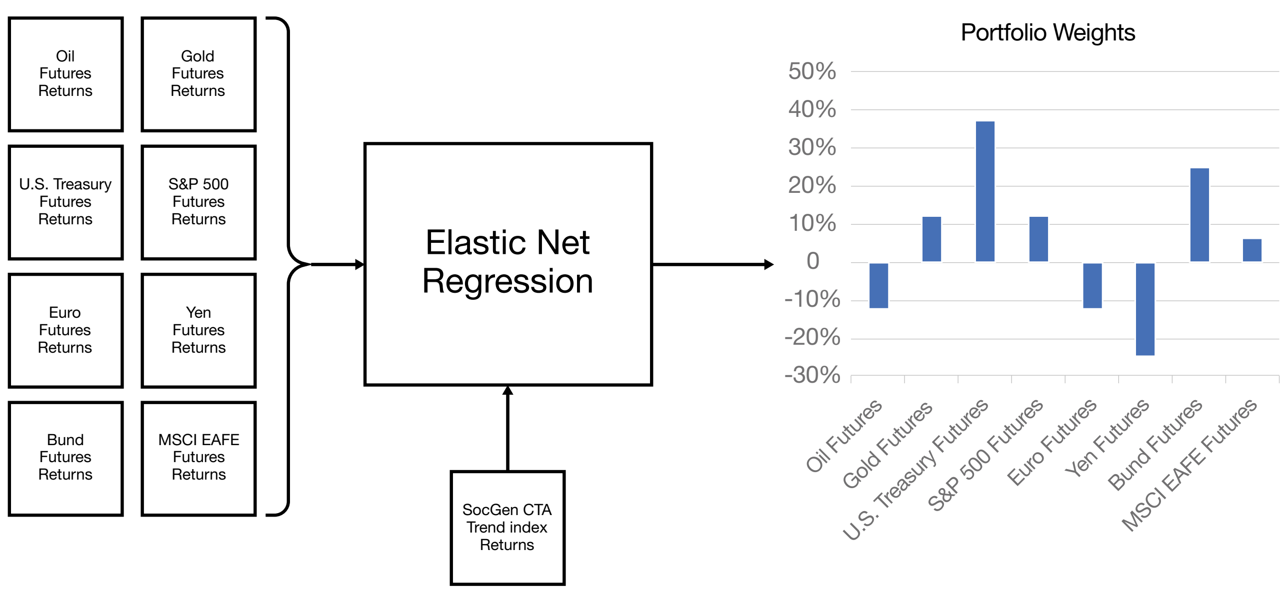
While Warren Buffett famously holds positions for decades, positions in trend-following managed futures funds can change rapidly. As a result, the replicating portfolio must be fit at each daily time-step, using returns to the index and the explanatory markets over the preceding days and weeks. Each model fit yields weights for a portfolio of representative markets which, if held over the term of the regression, minimize the squared difference between tracking portfolio returns and benchmark returns.

6 https://wholesale.banking.societegenerale.com/en/prime-services-indices/

Top-down replication is complicated by several factors. There is considerable diversity in the universe of markets traded in different funds, so exposures to underlying markets in the index is a function of the number of managers in the index that trade each market. The average holding period of positions is also not known, and this is further complicated by the fact that each position is rebalanced based on its own signals, which may or may not coincide with rebalancing of other markets on a given day.

In the academic literature, there are numerous approaches proposed for modeling dynamic portfolios[7], but this paper will focus on a method that utilizes robust linear regression. Elastic Net regression[8] was selected for top-down models because this modeling approach identifies the most important markets at play in each period, while simultaneously penalizing models that concentrate too heavily in any single market.

Figure 4. Elastic Net regression seeks a portfolio that minimizes the tracking error with the SG Trend Index at each point in time.



Source: Newfound Research. For illustrative purposes only.

First, the returns for each market are scaled to the same target standard deviation using a rolling 40-day exponentially weighted moving average of past returns. Then each day, the returns to the Trend index were regressed on the scaled returns of the universe of explanatory markets to find the portfolio that best matches the returns to the index. Individual

7 Recurrent neural networks, long-short-term-memory models, and Kalman filter regressions appear well suited to the problem because they explicitly capture the fact that yesterday's portfolio carries information about the likely constituents of today's portfolio. However, these models are burdened by other complexities that render them ill-suited for modeling trend-following managed futures strategies. In particular, since portfolios turn over every few weeks, the number of parameters that must be optimized in each model is large relative to the number of data points available for each fit.

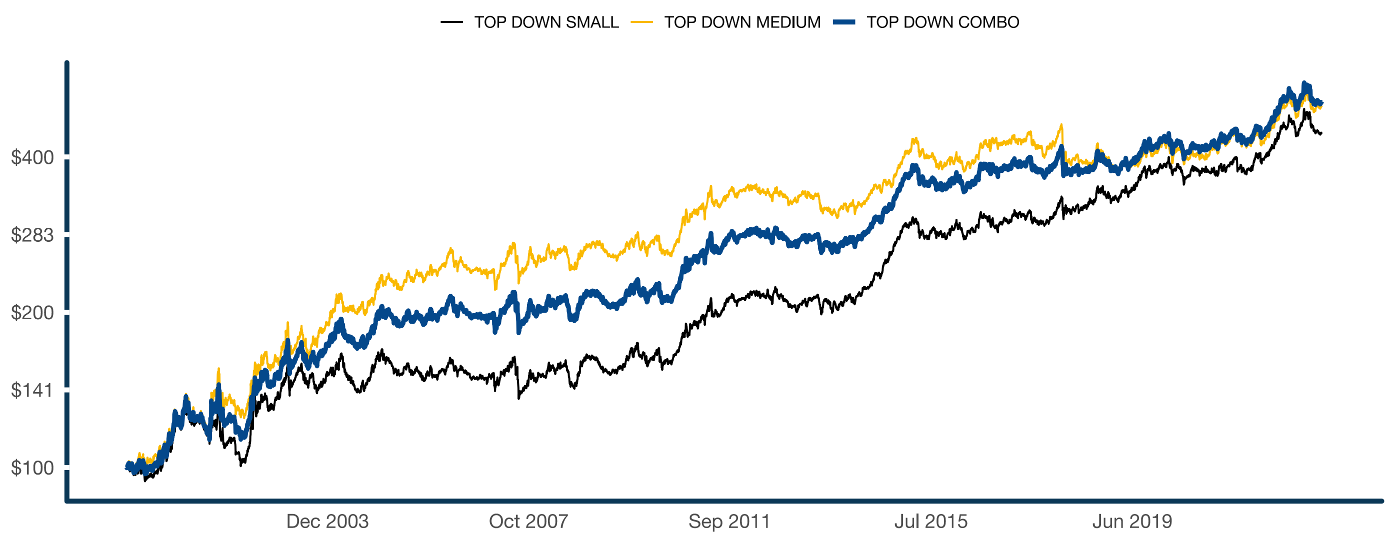
8 See Appendix – Robust Regression Primer for details on Elastic Net, LASSO and Ridge regression methods.

Elastic Net models were fit using rolling returns over each of the past 20, 25, 30, 35 and 40 days[9]. Finally, a linear model was fit on the output of the models fit at each lookback to determine the weights of the individual models in the final model.

There is a tradeoff between the number of markets used to explain the returns of the index, and the model fit. A larger universe of markets may explain a larger proportion of index returns, but the regression becomes less reliable as the number of explanatory variables becomes large relative to the number of observations used for the fit. A smaller universe may not span the full opportunity set available to managers in the index, but may produce more stable results given that there are at most 40 observations available for each fit.

Two representative baskets of explanatory markets were selected. A smaller basket consisted of 9 markets that represented broad exposures to equities, fixed income, commodities, and currencies. A larger basket included 27 markets with more granular exposures to the same sectors. When the weights at each time period were fitted using Elastic Net regression, a similar quality fit and performance over time were produced by both the small and large universes. However, periods of better and worse fit were exhibited during different periods, so that a better tracking portfolio was produced by combining the models than was observed by either model on its own.

Figure 5. Cumulative equity of Top-Down Trend Replication strategy GROSS excess returns, January 31st, 1990 – January 31st, 2023. SIMULATED RESULTS.



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Source: Futures data is from Refinitiv. Analysis performed by ReSolve Global. Simulation returns are total returns including roll yield, in excess of the funding rate and gross of slippage, commissions, and fees.

9 Lambda, the parameter that specifies the multiplier on the penalty function, was selected on the basis of the full-sample Sharpe ratio of returns generated from rolling regressions at each lookback horizon. K-fold cross-validation was used to validate the stability of the in-sample fit.

BOTTOM-UP REPLICATION

If the top-down approach is akin to trying to figure out which stocks Warren Buffett owns, the bottom-up approach is akin to trying to figure out which characteristics Warren Buffett uses to pick stocks.

Bottom-up replication is aimed at uncovering the underlying strategies that funds in the index are using to form portfolios. A combination of time-series momentum, price versus moving average, multiple moving average, or breakout systems are typically employed in trend-following strategies to identify market trends.

Trend-following managed futures funds may trade trends that evolve over lookback periods from a few weeks to a few years. Thirteen representative trend trading strategies were selected with lookbacks over representative time windows[10]. Specifically, trends were measured using total return[11] divided by standard deviation at each lookback to produce a z-score. The position in each market for each trend strategy was then a product of the z-score and the expected volatility of that market based on trailing 40 day exponentially weighted historical standard deviation. This produced 13 trend strategies x 27 markets = 351 combinations of market/strategy pairs.

A Ridge regression model was fit using the returns from these 351 strategies so that when the strategies were traded as a portfolio in the weights prescribed by the model, there was minimal difference between the returns of the replication portfolio and the index returns. Model weights were constrained to be long-only. Ridge regression was chosen over LASSO or Elastic Net because Ridge regression is well-suited for identifying all the relevant predictors, even if some of them may be false positives. Given that the strategies employed in trend-following funds are well documented in the literature, emphasis was placed on ensuring the inclusion of all relevant models at the expense of potentially including models that were used less frequently by trend-following managers.

K-fold cross-validation was used to assess whether strategy exposures change over time. Specifically, models were fitted on 90% of the data, and the selected strategies were run on the remaining 10% of the data. The out-of-sample strategy returns were then combined to simulate performance over the full history of the SG Trend Index. In addition, models were also fit on the full data sample, and the selected strategies were run on the full data set to generate a full simulation based on in-sample fit.

To compare the performance of the two simulations, the returns from both were scaled to the same target volatility using rolling 40-day exponentially weighted standard deviation. The out-of-sample simulation performed similarly to the simulation based on the entire data set, with a daily Pearson correlation of 0.997, suggesting models fit to the full dataset should be well calibrated to track the index in the future. The selected strategies were also largely consistent across sub-samples, indicating that trend-following futures managers have been consistent with the strategies and core markets traded over time.

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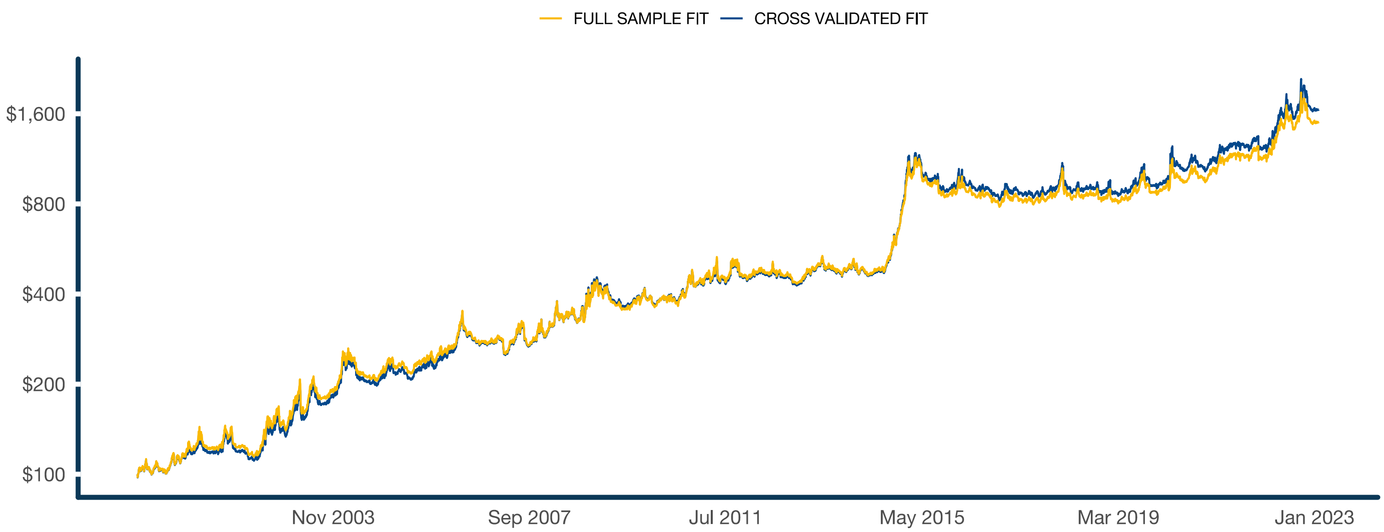
[10] Trend strategies were run on each market with lookbacks of 5, 10, 15, 20, 30, 40, 60, 90, 120, 180 and 260 trading days. The returns to these strategies were then used to explain the returns of the SG Trend Index.

[11] Price return plus roll return.

Figure 6. Cumulative equity full-sample and cross-validated Bottom-Up Trend Replication strategy GROSS excess returns, January 4th, 1990 – January 31st, 2023. SIMULATED RESULTS.



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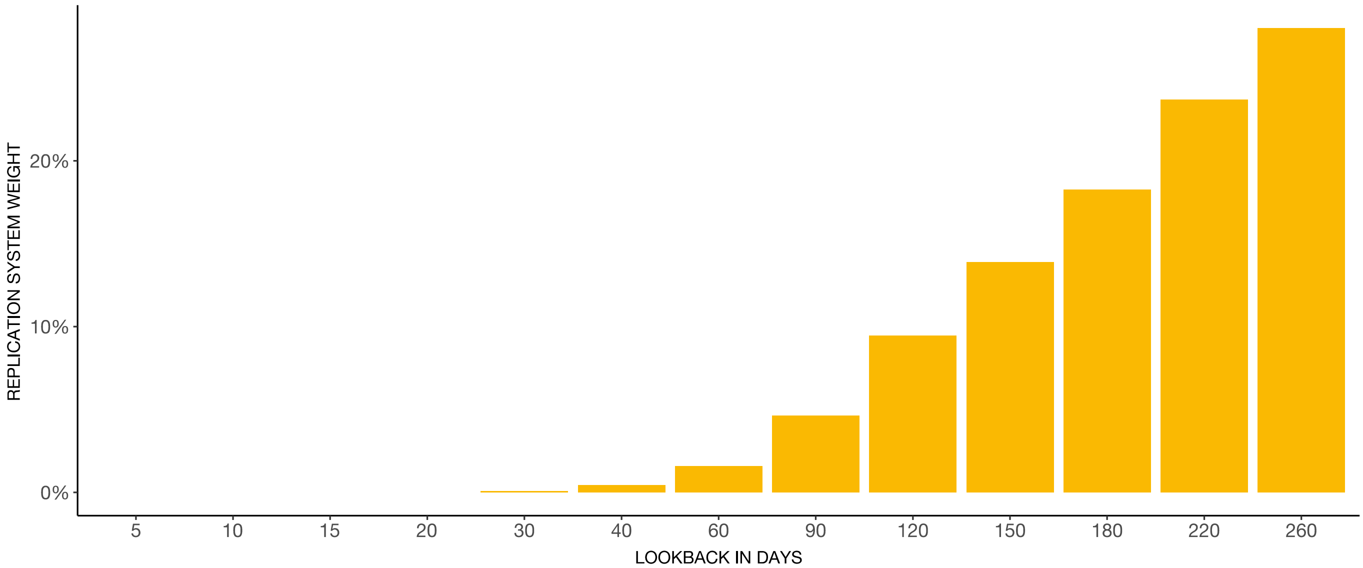
Source: Futures data is from Refinitiv. Analysis by ReSolve Global. Simulation returns are total returns including roll yield, in excess of the funding rate and gross of slippage, commissions, management and performance fees.

On average, the set of model/market pairs selected by the modeling process produced a replication strategy that exceeds a 0.8 correlation with the SG Trend Index, suggesting that the representative models span most of the models used in the index.

It is useful to examine which strategies were selected to best model the returns of the Trend Index. All the markets were selected for inclusion, and financial markets like currencies, equity and bond indices had greater weight than commodities. It was especially interesting to observe the weights that trend managers appear to express in trend strategies of different lookbacks. In aggregate, trend managers appear not to trade trends with lookbacks less than 30 days, and 98 percent of the weighting of selected strategies loaded on trend lookbacks of 90 days or greater. The models also imply that trend managers on average assign monotonically increasing weight to longer trend strategies.

Figure 7. Total trend system weights in the bottom-up trend replication strategy sorted on trend lookbacks in days, January 4th, 2000 – January 31st, 2023



Source: Data from Refinitiv. Analysis by ReSolve Global.

FINAL REPLICATION STRATEGY

The top-down and bottom-up strategies both create efficient tracking portfolios, each with its own strengths and weaknesses. While the top-down approach had a slightly inferior fit compared to the bottom-up method, it displayed a lower tracking error during crucial times in the historical data. Conversely, the bottom-up approach achieved a superior fit and overall performance, but it raises the concern that future managers may implement new strategies that are not represented by the replication strategies used.

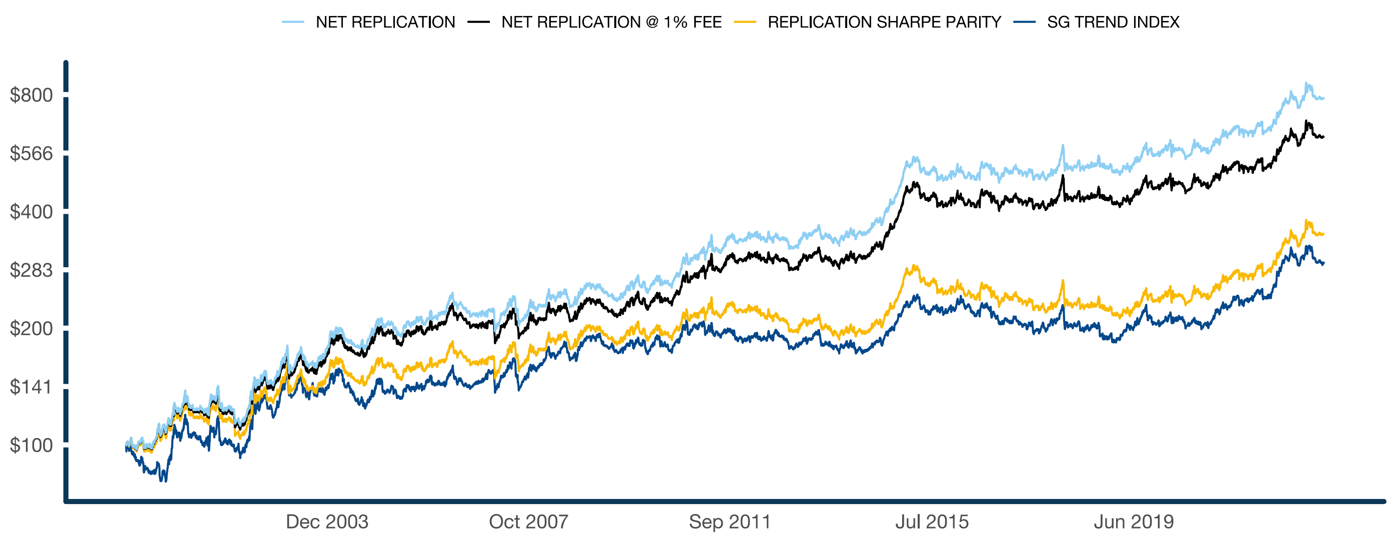
By combining the two methods, the final replication strategy can balance the strengths and weaknesses of both approaches and create a tracking portfolio that is both accurate and stable. The top-down and bottom-up strategies are not perfectly correlated, so a combination produced higher performance than either approach on its own. Combining the methods also improves the long-term correlation between replication and benchmark returns.

The final Replication strategy gives 50% weight to the bottom-up replication and 50% weight to the top-down strategy. The top-down strategy gives equal risk weight to the replication on the small universe of markets, and 50% weight to the replication on the large universe. Both the bottom-up and top-down replication weights are first scaled to target 20 percent long-term average volatility so that the combination accrues 50 percent of risk from each strategy. The combined weights are then smoothed using a 5-day exponential moving average to optimize trading frictions.

Figure 8 compares the performance character of the Replication strategy against the SG Trend Index. Note that the SG Trend Index is net of all costs including management fees and performance fees while the Replication strategy is net of estimated trading commissions and slippage but gross of all fees ("Net Replication strategy"). While large institutions may be able to implement the Replication strategy internally for nominal cost, many investors would expect to pay a fee for access to the strategy. A version of the Net Replication strategy less a representative 1 percent annual fee is also provided for illustration. Note that we deducted the return on T-bills from the SG Trend Index returns to be consistent with the returns of the Replication strategies, which are also net of cash returns.

In an effort to illustrate how the Replication strategy tracks the return trajectory of the SG Trend Index over time, a Sharpe Parity Replication strategy was created by scaling the returns of the Net Replication strategy to equal the Sharpe ratio of the Trend Index over all rolling 3-year periods. This preserves most of the correlation character of the Replication strategy relative to the Trend Index but aligns the equity lines in the chart to gain a better understanding of how the Replication strategy tracks the index. As we can see from Figure 8, the Replication strategy equity line is very similar to the SG Trend Index, implying that the Replication strategy is a close proxy for investment in the benchmark Index.

Figure 8. Cumulative equity of excess returns for the Net Replication strategy (GROSS of fees), Net Replication strategy (NET of 1 percent annual fee), the Sharpe Parity Replication strategy, and the SG Trend Index (NET of fees), January 31st, 2000 – January 31st, 2023. SIMULATED RESULTS.



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Source:
Futures data is from Refinitiv. Analysis by ReSolve Global. Simulation returns are total returns including roll yield, in excess of the funding rate. NET REPLICATION is net of estimated trade slippage and commissions, but gross of all fees. NET REPLICATION @ 1% FEE is net of estimated trade slippage and commissions, and a 1% annual fee charged daily. NET REPLICATION SHARPE PARITY is net of estimated trade slippage and commissions, and scaled to target the same Sharpe ratio as the SG Trend Index over all rolling 3-year periods. SG Trend Index returns are net of all transaction costs and fees, and in excess of the 3-month US Treasury bill yield.

Table 3. Performance statistics for the Net Replication strategy (GROSS of fees), Net Replication strategy (NET of 1 percent annual fee), the Sharpe Parity Replication strategy, and the SG Trend Index (NET of fees), January 31st, 2000 – January 31st, 2023. Excess returns. SIMULATED RESULTS.

	NET REPLICATION	NET REPLICATION @ 1% FEE	SG TREND INDEX
Start Date	Feb 01, 2000	Feb 01, 2000	Feb 01, 2000
Annualized Return	9.13%	8.08%	4.65%
Annualized Volatility	13.40%	13.40%	12.90%
Sharpe Ratio	0.72	0.65	0.42
Sortino Ratio	1.00	0.90	0.57
Max Drawdown	-21.20%	-21.50%	-24.80%
Correlation to SG TREND	0.86	0.86	1.00

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Some of you may be wondering how the Net Replication strategy would have performed if it had been subject to the same fees as the funds in the SG Trend Index. To compare apples to apples, we calculated the returns for the Net Replication strategy after subtracting a 2% management fee and a 20% performance fee charged quarterly (2 & 20).

In simulation, the Net Replication strategy earned an annualized excess return of 9.13% before fees, from the inception of the SG Trend Index on January 31st, 2000 through January 31st, 2023. After taking fees into account, the Net Replication strategy produced an annualized excess return of 5.59%, which is higher than the 4.65% annualized excess returns of the SG Trend Index over the same time period.

The 3.54 percentage points per year difference between the compound returns to the Net Replication strategy and the Net Replication strategy net of 2 & 20 fees suggests the possibility of fee alpha. This means that by removing the fees charged by funds in the index, the Net Replication strategy has the potential to generate higher returns.

CONCLUSION

In this paper, we have explored two replication methods for trend-following benchmark indices and evaluated their effectiveness in creating tracking portfolios that accurately capture the performance of the index. Our analysis reveals that both top-down and bottom-up replication methods can create efficient tracking portfolios, each with its own strengths and weaknesses. The bottom-up replication method aims to uncover the underlying strategies used by trend-following managed futures funds to form portfolios, while the top-down replication method identifies the most important markets at play in each period.

We find that the final Replication strategy, which gives 50% weight to the bottom-up replication and 50% weight to the top-down replication, strikes a reasonable balance between accuracy and stability. By combining the two methods, the strategy has been able to capture the broad exposures to equities, fixed income, commodities, and currencies that are present in the index while also identifying the underlying strategies used by trend-following managed futures funds. Moreover, our analysis shows that the set of model/market pairs selected by the modeling process produced a replication strategy that exceeds a 0.85 correlation with the SG Trend Index, suggesting that the representative models span most of the models used in the index.

Overall, our findings indicate that trend-following replication strategies have good potential to track the performance of benchmark trend indices while also outperforming the index over the long-term due to lower fees. By using a combination of top-down and bottom-up replication methods, investors can create tracking portfolios that accurately capture the performance of the index while also minimizing the risk of underperformance due to changes in the underlying strategies used by trend-following managed futures funds.

APPENDIX - ROBUST REGRESSION: A PRIMER

In statistical modeling, bias and variance are two important concepts that reflect the quality of the model. Bias refers to the difference between the expected value of the model's predictions and the true value of the outcome being predicted. A model is said to be biased if it consistently overestimates or underestimates the true value of the outcome. On the other hand, variance refers to the amount by which the model's predictions vary for different training sets. A model with high variance is sensitive to small fluctuations in the training data, which can lead to overfitting and poor generalization to new data.

The bias-variance tradeoff is the balancing act that is required when developing a statistical model. A model that is too simple may have low variance but high bias, which means that it consistently underestimates or overestimates the true value of the outcome. Conversely, a model that is too complex may have low bias but high variance, which means that it fits the training data very closely but may not generalize well to new data. Finding the right balance between bias and variance is crucial to developing a model that is accurate and generalizable.

Type 1 and Type 2 errors are also important concepts in statistical modeling, particularly in hypothesis testing. A Type 1 error occurs when a null hypothesis is rejected even though it is actually true. In other words, the hypothesis test incorrectly concludes that there is a significant effect when there is not. A Type 2 error occurs when a null hypothesis is not rejected even though it is actually false. In other words, the hypothesis test incorrectly concludes that there is no significant effect when there is one.

The tradeoff between Type 1 and Type 2 errors is another balancing act that is required when conducting hypothesis testing. Reducing the risk of one type of error often increases the risk of the other type of error. For example, lowering the significance level of a hypothesis test (thereby reducing the risk of a Type 1 error) will increase the risk of a Type 2 error.

Traditional Ordinary Least Squares (OLS) regression suffers from several well-known issues, which make it ill-suited to many modeling tasks. When predictors are highly correlated, as is often the case in real-world data, OLS regression can result in unstable coefficient estimates and a lack of interpretability in the model. OLS regression is more prone to overfitting, which occurs when the model is too complex and fits the training data too closely. Overfitting can lead to poor performance on new data and reduced interpretability. Also, OLS regression includes all predictors in the model, even those that may not be relevant or significant.

Ridge regression, LASSO regression, and Elastic Net regression are robust regression techniques that overcome many of the weaknesses of traditional OLS regression. These techniques use regularization, which adds a penalty term to the regression objective function to allow data scientists to more explicitly manage the tradeoff between bias and variance, and Type 1 and Type 2 error in statistical modeling.

Ridge regression introduces a penalty term that adds a multiple of the L2-norm of the coefficients to the objective function. This penalty term shrinks the coefficient estimates towards zero, reducing the variance of the estimates and minimizing overfitting. Ridge regression can help to reduce the Type 2 error rate, which means it can help to identify true predictors that are correlated with the outcome. However, Ridge regression has the potential to introduce bias into the coefficient estimates, as it may underfit by shrinking them towards zero.

LASSO regression introduces a penalty term that adds a multiple of the L1-normof the coefficients to the objective function. This penalty term forces some of the coefficients to be exactly zero, effectively performing variable selection. LASSO can help to reduce the risk of overfitting and reduce the number of predictors in the model, but it can also introduce bias into the coefficient estimates. Specifically, small perturbations in sample data may prompt LASSO models to select very different sets of predictors. LASSO can also help to reduce the Type 1 error rate, which means it can help to identify predictors that are truly significant and not false positives.

Elastic Net regression combines Ridge and LASSO regression by adding a penalty term that is a weighted sum of Ridge and LASSO penalties. This penalty term can help to reduce both the Type 1 and Type 2 error rates and provide a better balance between bias and variance. Elastic Net can help to reduce the risk of overfitting, and also reduce the number of predictors in the model.

The choice of whether to employ Ridge, LASSO or Elastic Net regression depends on a number of factors. If a modeler is concerned about selecting too narrow a set of predictors, or that an effect may not be stable across samples, Ridge regression may be preferred. If a modeler is confident of stable effects and is more concerned with selecting a subset of predictors, LASSO regression may make more sense. If a modeler is uncertain about the stability of model effects and has no preference for Type 1 or Type 2 error, then Elastic Net may be optimal.

In summary, Ridge regression, LASSO regression, and Elastic Net regression all manage the tradeoff between bias and variance by using regularization. Ridge regression can help to reduce the Type 2 error rate and prevent overfitting, but may introduce bias. LASSO regression can help to reduce the Type 1 error rate and perform variable selection, but may also introduce excess variance. Elastic Net regression sometimes provides a better balance between bias and variance and can help to reduce both Type 1 and Type 2 error rates.

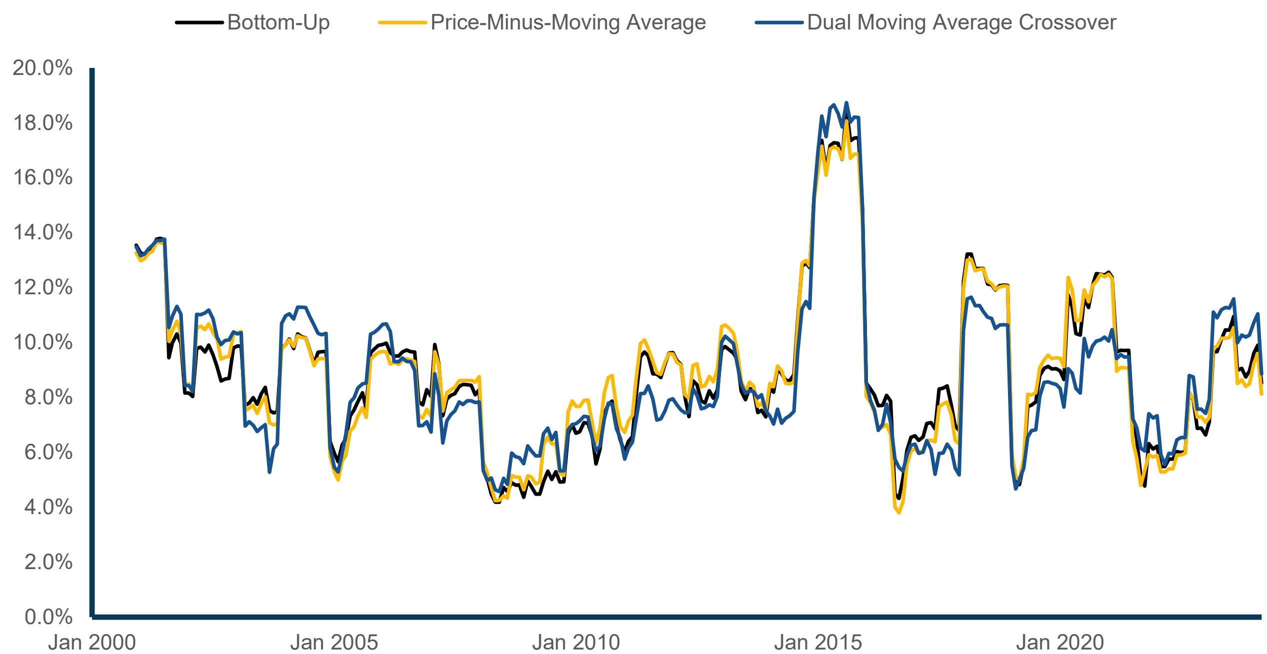
ADDENDUM

Do different trend signals change the fit of the bottom-up replication?

The bottom-up methodology utilizes a total return-oriented method (TR) of creating trend signals. One potentially prudent question is whether the trend methodology selected materially changes the program's ability to track the benchmark index.

Below, we plot the tracking errors of bottom-up methodologies trained for price-minus-moving-average crossover signals (PMAC), dual moving-average crossover signals (DMAC).

Figure 1. Tracking Errors of Varying Bottom-Up Trend Signals, January 31st, 2000 – March 31st, 2024



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Source: Futures data is from Refinitiv. SG Trend Index data is from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global. Simulation returns are total returns including roll yield, in excess of the funding rate and gross of slippage, commissions, and fees.

We find that the differences are largely noise, with none of the differences being statistically significant over the period, suggesting that all three methods are equally viable with respect to replication.

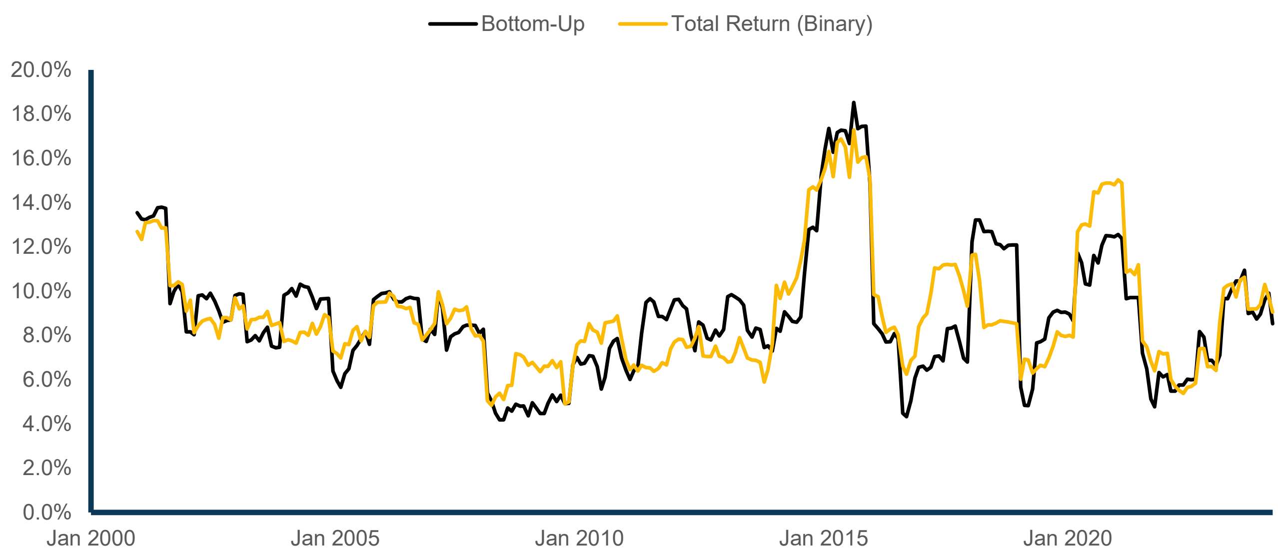
Does a continuous versus binary trend signal change the fit of the bottom-up replication?

When creating a trading signal, a common decision that will need to be made is the choice to utilize a *binary* or a *continuous* signal. The methodology used in the original paper chose to implement a continuous signal to incorporate both the direction and the strength of the trend.

To analyze how a binary signal may impact the ability to track the benchmark, instead of utilizing the z-score to establish a position, we find the sign (+1 for a long position, and -1 for a short position) of the total return for each contract and multiply this value by the expected volatility for the position in each contract.

The below figure shows the tracking error of this binary implementation alongside the continuous version.

Figure 2. Tracking Error of a Binary Versus Continuous Trend Signal, January 31st, 2000 – March 31st, 2024



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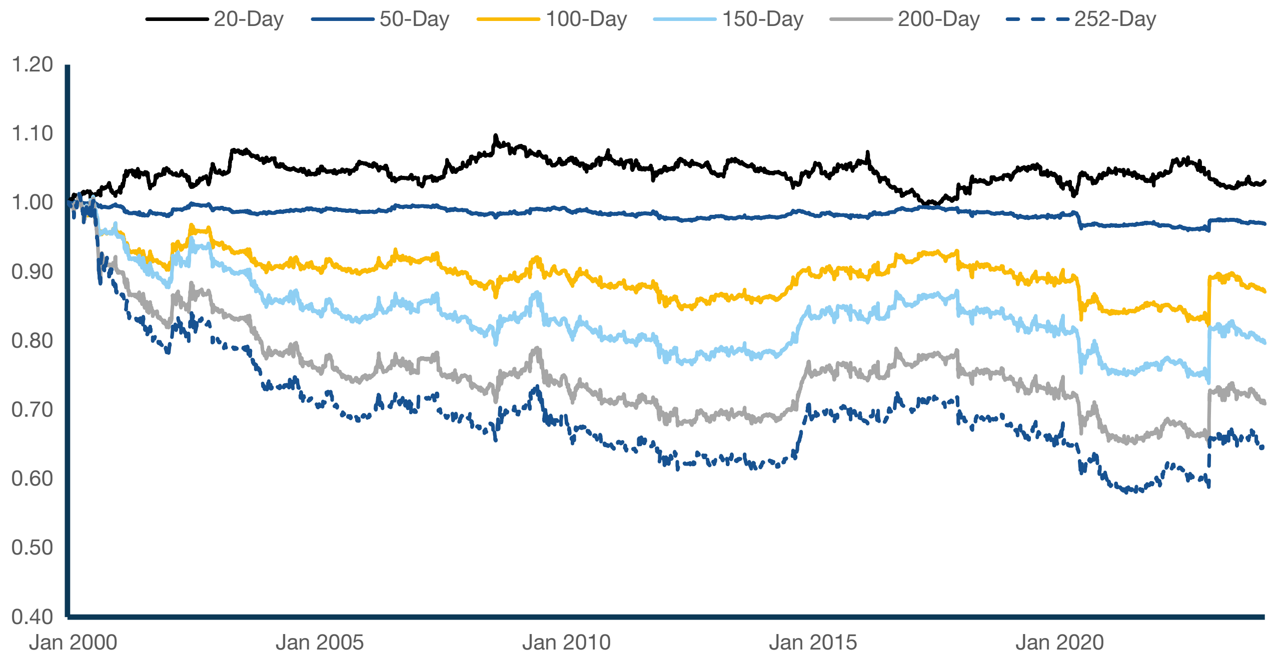
While there are short periods in the sample that favor one implementation over another, on average, we find that there are no significant differences between either implementation.

How sensitive is the bottom-up replication to the volatility lookback?

The original methodology employed a 40-day, exponentially weighted lookback to estimate position-level volatility scaling. It may be prudent, then, to assess how sensitive the program is to the selection of volatility lookback.
Below we show the relative performance of a 20-, 50-, 100-, 150-, 200-, and 252-day volatility lookback, compared to the 40-day implementation.

Figure 3. Relative Returns of Varying Levels of Contract-Level Volatility Scaling, January 31st, 2000 – March 31st, 2024



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An interesting pattern emerges, where the utilization of a longer-term lookback seems to have a negative impact on performance. Since the position sizes within the trend-following portfolio are a function of the volatility, having a shorter lookback window allows for the position sizes to more rapidly react to changing volatility.

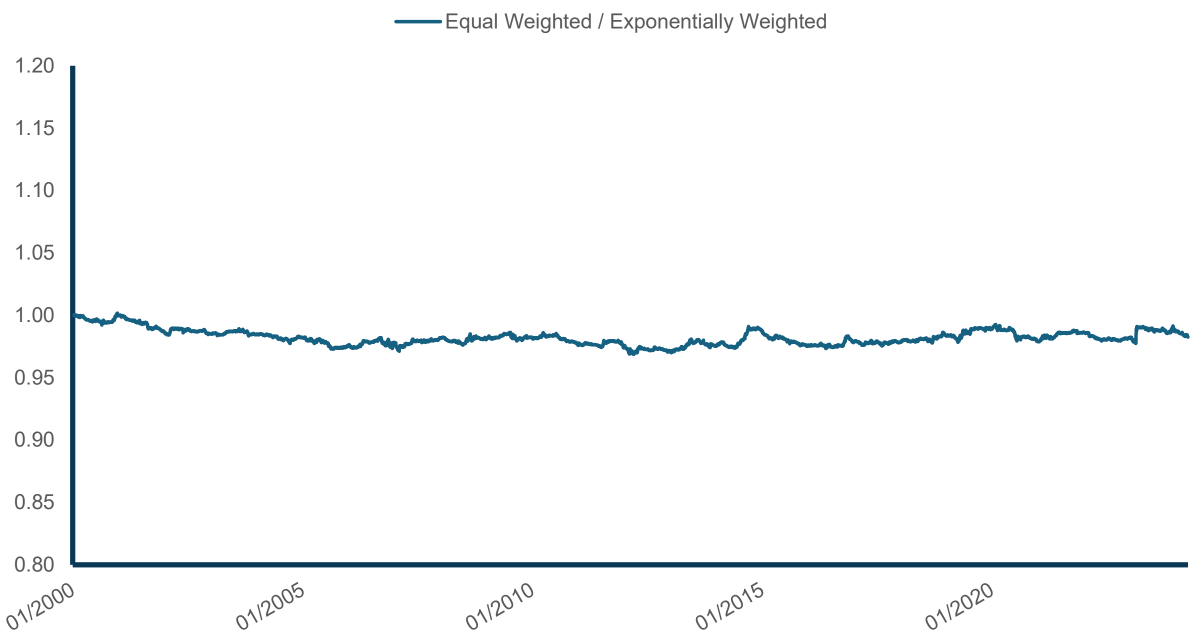
From a risk management perspective, increased sensitivity to volatility changes may seem prudent. However, increased sensitivity assumes that recent realized volatility is more predictive of future volatility than longer-term measures, which may not always be the case. For example, prior to March 2023, volatility in the fixed income space was relatively low. Shorter-term lookbacks, therefore, created larger positions in interest rate related contracts and were therefore more exposed to the historic move in interest rates.

Despite the perceived performance differences, it should be noted that the relative performance has been largely flat since 2005, with the largest differences occurring in 2000-2005. None of these iterations are statistically significant.

Do equally weighted versus exponentially weighted returns impact the bottom-up replication?

In the original methodology, an exponentially weighted return measure is used, putting more weight on more recent returns, as opposed to a more common, equally weighted total return measure. Does this choice materially impact the results, and additionally, does this change the loadings to the underlying trend-following systems?

Figure 4. Relative Returns of Equal-Weight Versus Exponentially Weighted Total Return, January 31st, 2000 – March 31st, 2024



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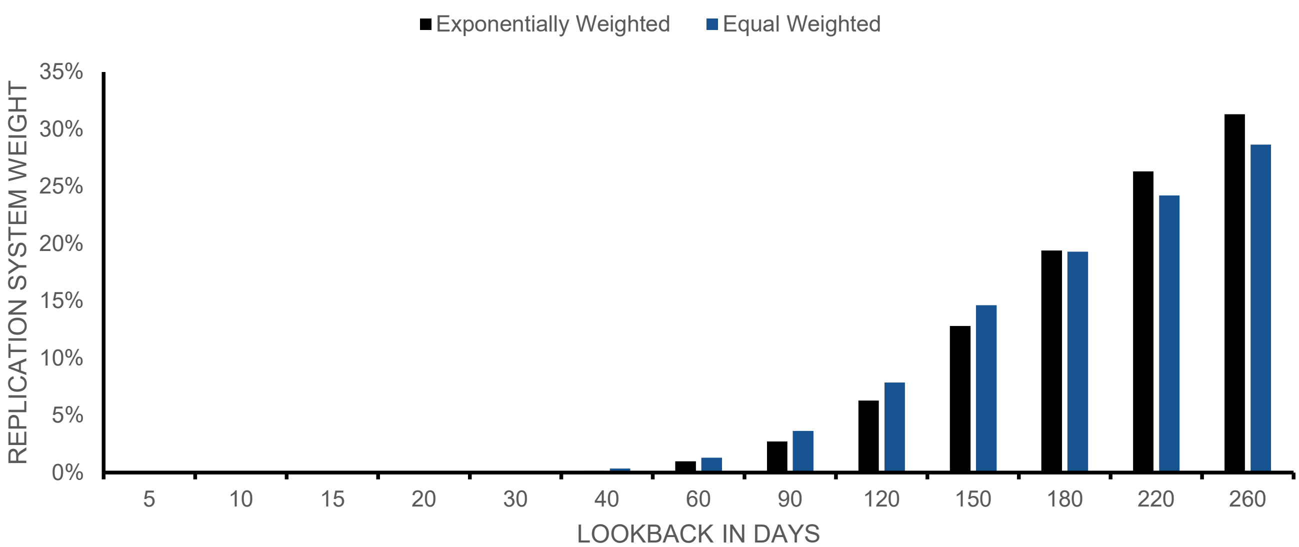
Again, the difference in returns amounts to mostly noise, with the difference in performance not being statistically significant.

If we analyze the bottom-up loadings based on the time horizons we find that the equal-weighted volatility permutation holds a nominally shorter time horizon, with the equal-weight having a weighted average lookback of 198 days, while the exponentially weighted version has a weighted average lookback of 204 days.

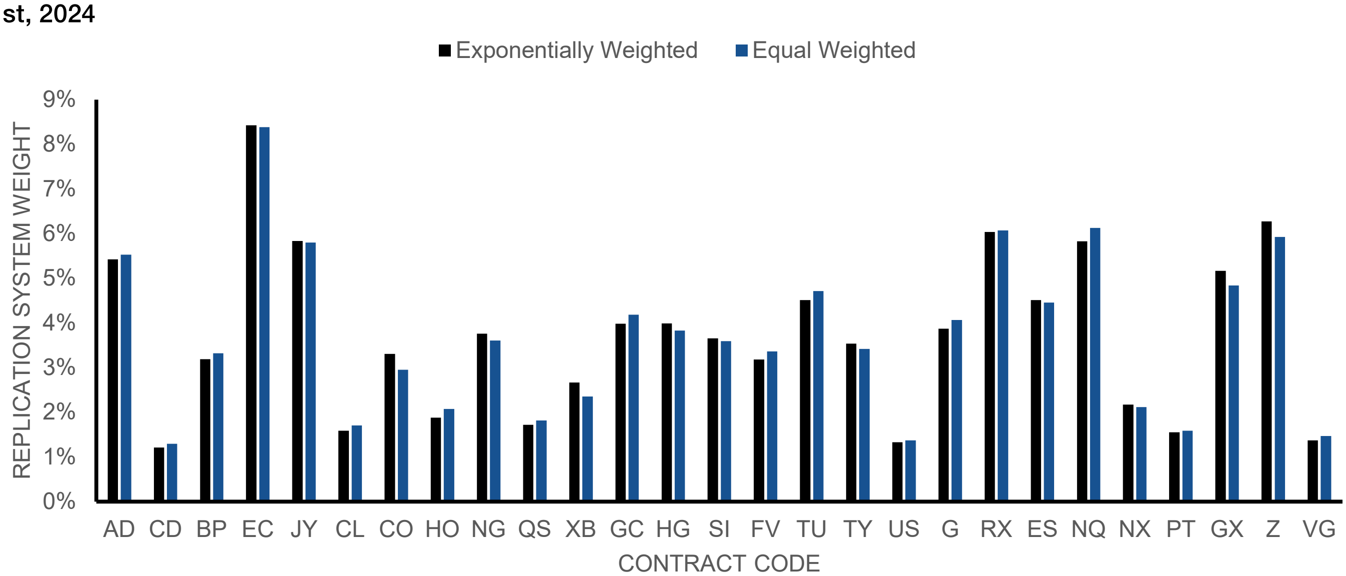
Figure 5. Total Return Method Bottom-Up System Weights Sorted on Trend Lookbacks in Days, January 31st, 2000 – March 31st, 2024



Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

Across contracts, however, we find little-to-no material differences in the loadings.

Figure 6. Total Return Method Bottom-Up System Weights Sorted on Individual Contracts, January 31st, 2000 – March 31st, 2024

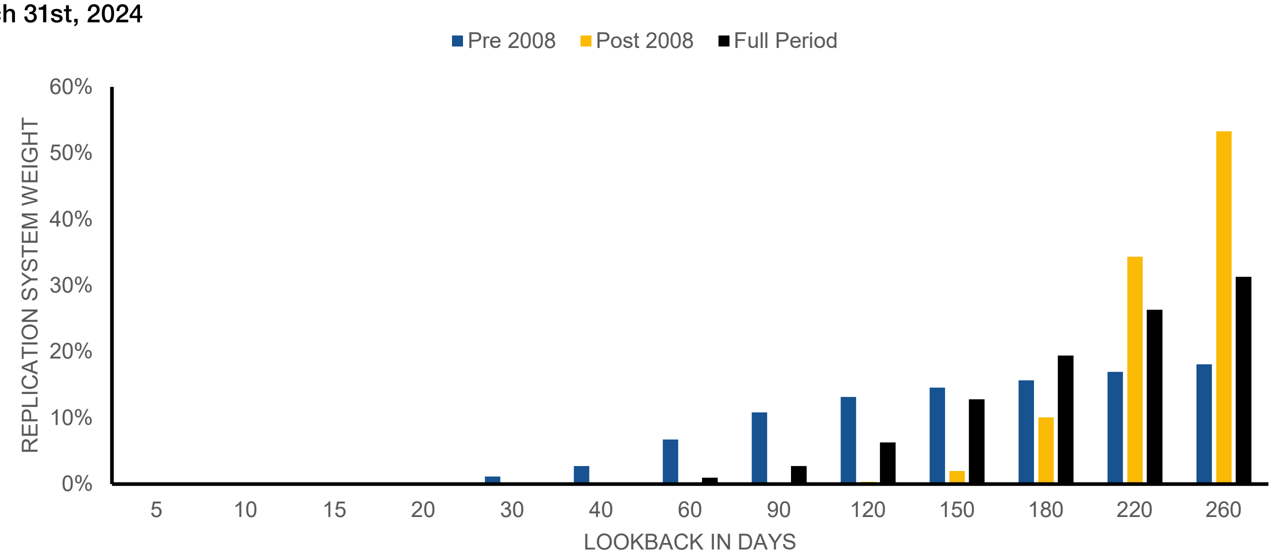


Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

How do the bottom-up loadings change pre- and post-2008?

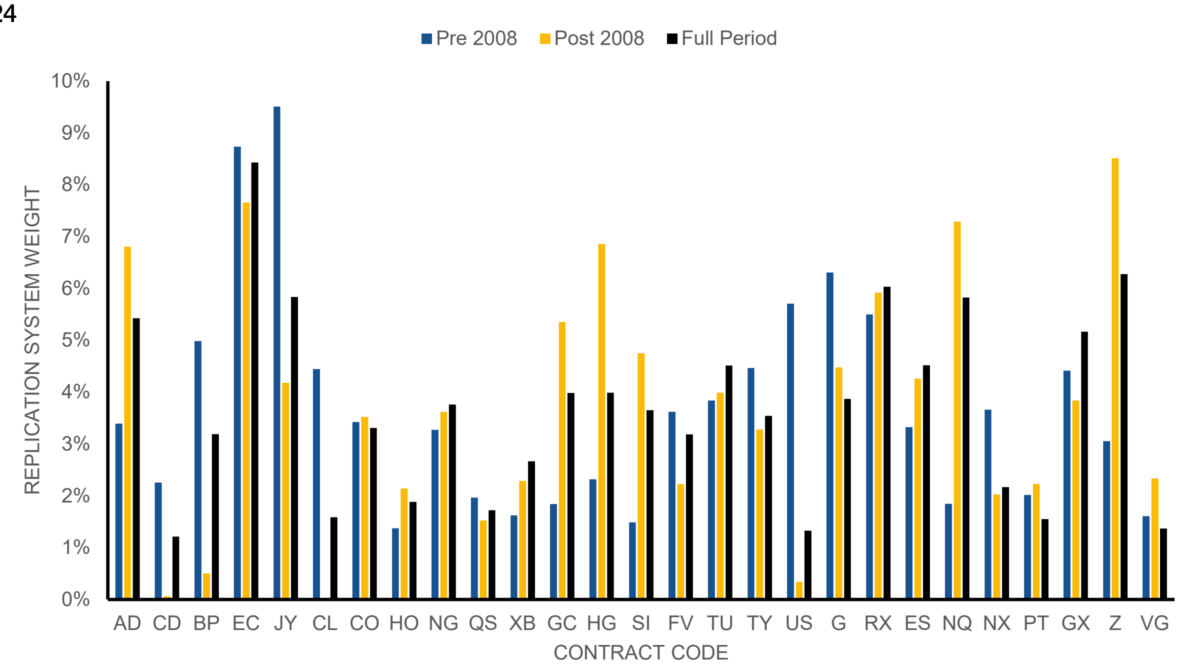
If we fit the bottom-up models using only data up to October 31, 2007, or using only data after March 31, 2009, we find that there are some stark differences in both the contracts, as well as the length of the horizons.

Figure 7. Pre- and Post- 2008 Bottom-Up System Weights Sorted on Trend Lookbacks in Days, January 31st, 2000 – March 31st, 2024



Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

Figure 8. Pre- and Post- 2008 Bottom-Up System Weights Sorted on Individual Contracts, January 31st, 2000 – March 31st, 2024



Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

Regarding the trend lookback, we find that the fit post-2008 holds a higher weight to longer-term lookbacks than the pre-2008 fit, which has a far more even loading on the lookbacks greater than 90 days. This aligns with a 2023 analysis from Quantica, that found "… that the trend-following industry apparently sought to capture faster trends until the mid-2000s, and likely operated with a longer average lookback from 2007 onward."

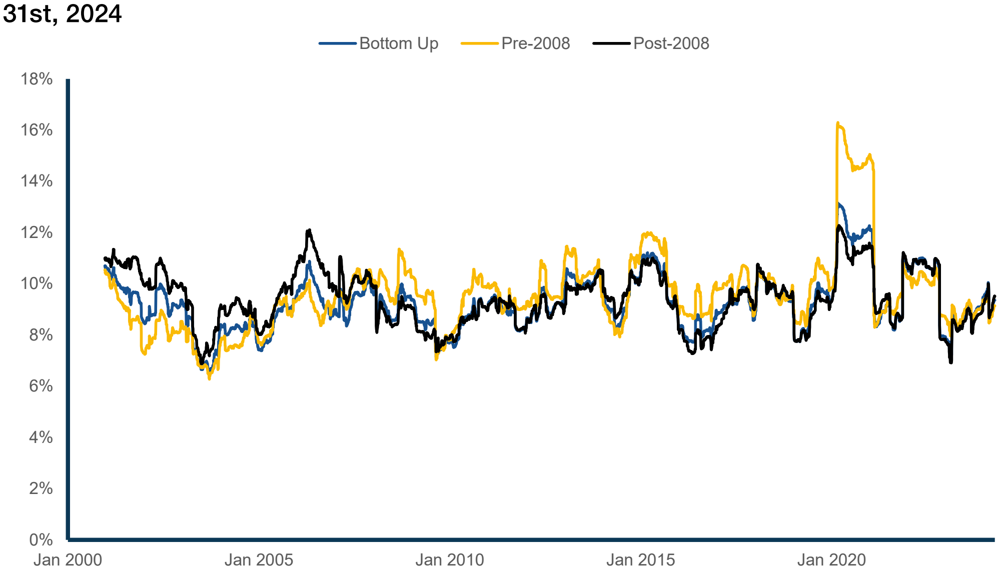
A subtle nuance to this analysis is that a market's risk weighting will largely be determined by three factors: (1) the risk weight in which the underlying managers of the SG Trend Index traded it; (2) that market's contribution to performance over the period; and (3) that market's correlation to other markets traded over the period. Our process seeks to determine the first point while the second and third serve as potential sources of noise.

For example, consider the case where all managers have significant risk weight to Gold, but Gold goes through an extended period of exhibiting no trends, and therefore contributes little to overall performance. Without more data, it would be impossible to determine whether Gold was traded at all! Conversely, consider the situation where a contract contributes significantly to returns, but is highly correlated to another contract or theme (for example, commodities and U.S. dollar exposure in the 2000's). In such a scenario, determining which contracts were traded, and in what size, can be difficult.

So, while it may appear that the weights to some contracts pre- and post-2008 are substantially different, these differences may be explained by the sources of noise. Hence our preference to use the full period in-sample period for training, rather than use a rolling-window approach.

Despite these differences in system loadings between the pre- and post-2008 periods, the resulting correlations to the full model remain high, with the pre- and post-2008 correlations being 0.95 and 0.98, respectively. In Figure 9, we show the 252-day tracking errors of the Bottom-Up replication, alongside the pre- and post-2008 replication models relative to the benchmark index.

Figure 9. 252-Day Tracking Errors of Pre- and Post- 2008 Model Fits and the Bottom-Up Replication, January 19th, 2000 – March 31st, 2024



Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

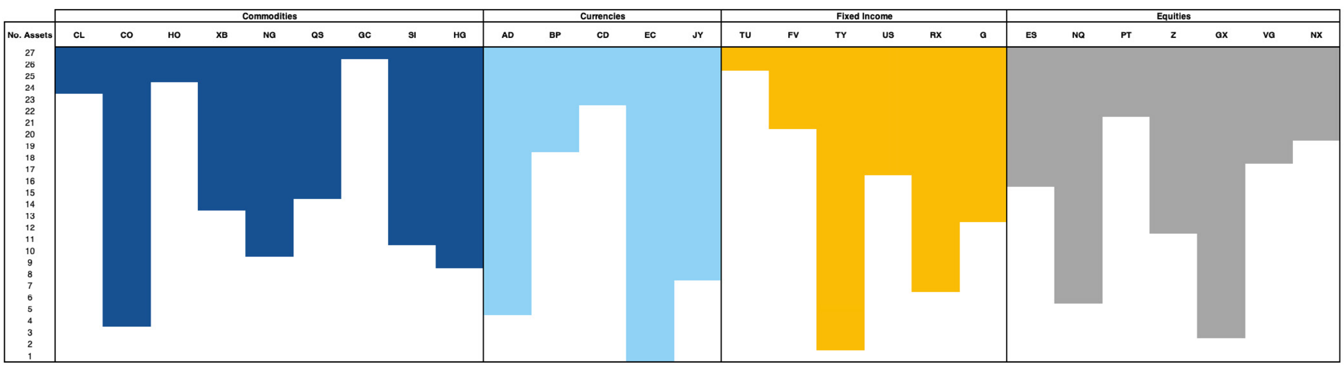
Which contracts, and how many, are most important in fitting the index?

In considering which assets to include in the initial replication paper, contracts were selected to represent equity, bond, currencies, and commodities, and the most liquid contracts were selected as the cohort. The top-down replication methodology also consisted of a “small” universe of 9 futures contracts, as well as a “medium” universe. Out of these contracts, how many are necessary in total, and which futures contracts hold the highest influence in the fit.

To test this question, both the bottom-up and top-down replications were run, beginning from the full 27 contract universe, then dropping each contract and re-running to find the contract with the smallest impact to tracking error relative to the target index. The contract that added the smallest amount of tracking was then dropped, and the process was repeated with one fewer contract until a single asset remained.

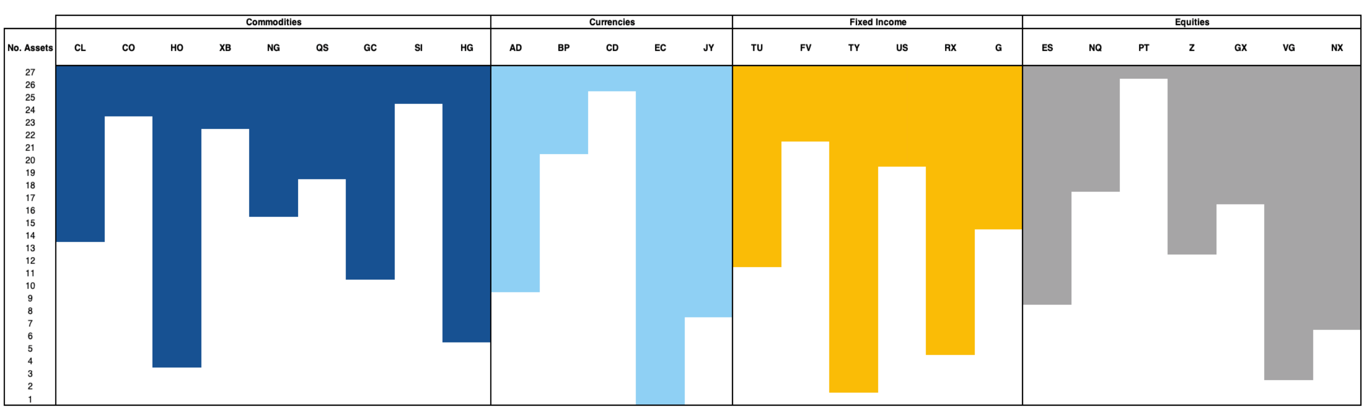
The below figures show the results of this exercise for the bottom-up and top-down replications, respectively.

Figure 10. Bottom-Up Contract Inclusion Based on Tracking Error Impact, January 19th, 2000 – March 31st, 2024



Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

Figure 11. Top-Down Contract Inclusion Based on Tracking Error Impact, January 19th, 2000 – March 31st, 2024

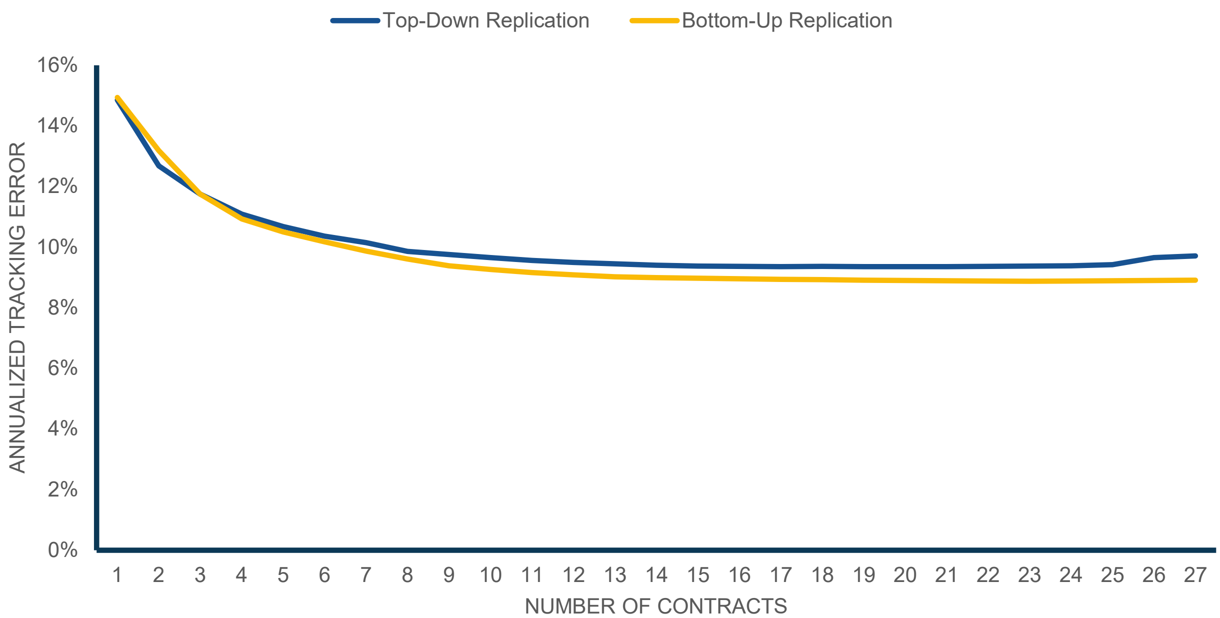


Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

As we can see, one of the key takeaways is that at least one asset from each of the asset classes is necessary to create a fit. For both replication versions, until there are only three assets allowed in the universe, there is a representative contract from each of the asset classes.

In Figure 12, we illustrate the impact of varying the number of contracts on the tracking error relative to the benchmark index. From this figure, we find that there is a point at which adding additional contracts bears no significant marginal benefit, aside from statistical noise.

Figure 12. Replication Tracking Errors with Differing Contracts, January 19th, 2000 – March 31st, 2024



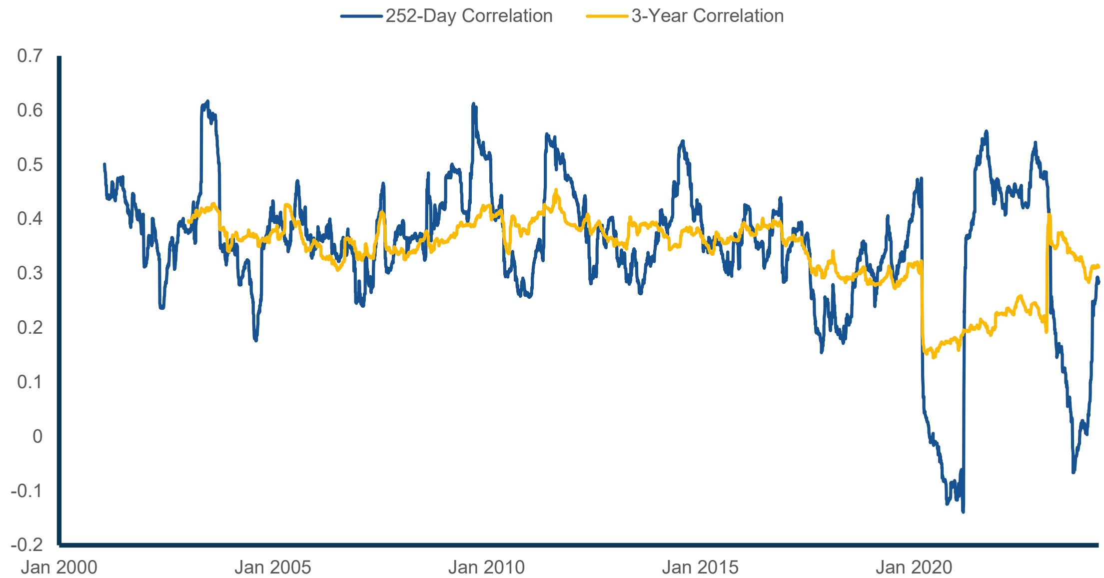
Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

What is the Relationship Between Top-Down and Bottom-Up Replication?

One interesting aspect of the interaction between the Top-Down and Bottom-Up approaches, is the relationship between their tracking errors. While both methods are crafted in the pursuit of replicating a provided index, each method holds its own unique weaknesses, and from a theoretical perspective, these weaknesses should be diversifying in nature.

In Figure 13, we show the rolling correlations between the excess returns above the designated index for both the Top-Down and Bottom-Up approaches.

Figure 13. Tracking Error Correlation for Both Methods, January 19th, 2000 – March 31st, 2024

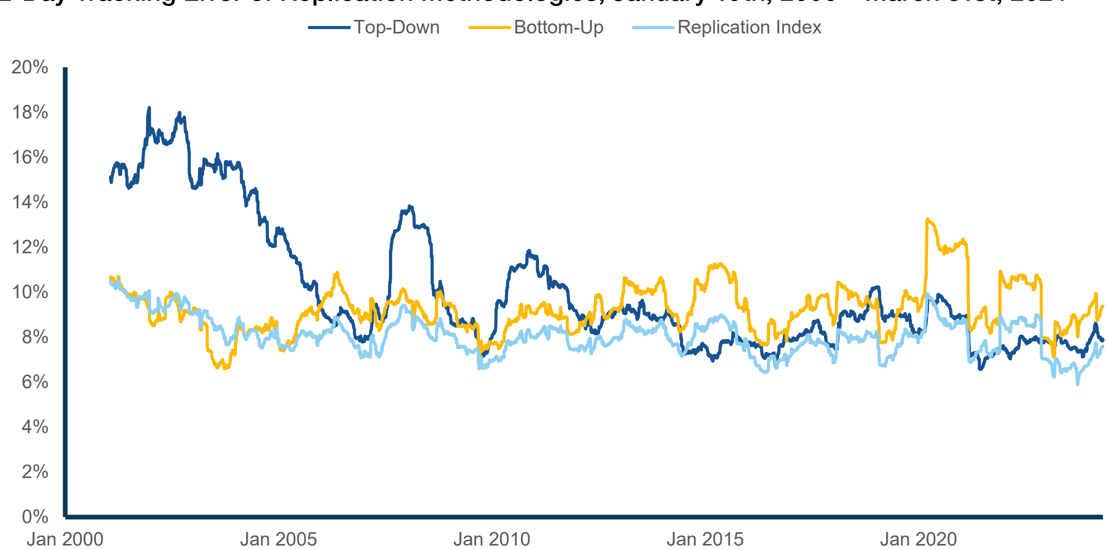


Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

As we can see, the correlation between the two methods consistently remains around the 0.3-0.5 mark, indicating that the utilization of both methods diversifies the overall strategy's tracking error.

If we analyze the tracking error of the individual strategies, alongside the 70/30 combination, we find that total replication index consistently holds a lower tracking error than either of the two strategies individually.

Figure 14. 252-Day Tracking Error of Replication Methodologies, January 19th, 2000 – March 31st, 2024



Source: Data from Refinitiv. SG Trend Index Data from BarclayHedge. Calculations by Newfound Research and ReSolve Asset Management Global.

From the above figures, it becomes clear that while both methodologies seek to accomplish the same goal, the combination of the two can improve upon the overall program's ability to replicate the index.

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Equity line results show the growth of $100 assuming the purchase and sales of securities were executed at their daily closing price. Profits are reinvested and the simulation reflects assumptions regarding commissions, transaction costs of buying and selling securities, management fees and performance fees as described in the relevant sections. Any strategy carries with it a level of risk that is unavoidable. No investment process can guarantee or achieve consistent profitability all the time and will necessarily encounter periods of extended losses and drawdowns.

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