A Commodity Investing Strategy to Modify the 60-40 Allocation Scheme

by

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Abstract

Strategies to add commodities as an alternative diversifier to a core 60% equity / 40% fixed-income portfolio have produced lackluster performance. These strategies, intended to generate stable investment returns with acceptable levels of volatility, have not addressed significant paradigm shifts in the commodities market, including backwardation-contango oscillation, time-varying correlation among major asset classes, and a massive flow of funds chasing long or short-only strategies with high fees and high transaction costs related to periodic rolls. This paper develops an all-weather investment strategy that addresses these paradigm shifts. The strategy - Liquid Alternative Commodity Index (LACI) - incorporates a long/short and fully invested monthly positioning rule for the commodities market, along with a simple proprietary trend algorithm to determine the following month's position. Risk-adjusted performance shows that our liquid commodity index performs better than many brand name CTA's, hedge funds, commodity-based listed ETFs, ETNs, and mutual funds. Moreover, when LACI is added to a mix of equity and fixed income investments, it offers superior diversification benefits and performance.

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* Jahangir Sultan is Gibbons Professor of Finance. We thank anonymous reviewers for their valuable comments. We are responsible for all remaining errors. Preliminary. Please do not quote without permission. **Corresponding author: Raymond Murphy is the Chief Investment Officer of RTM Alternatives, LLC, a commodity advisory firm. **Disclosure**: LACI is currently a part of the S&P Global Universe of Indexes. Standard & Poor's Dow Jones Index group is the calculation agent and Benchmark Administrator for the Market State Dynamic Commodity Indexes (tickers: MSDCIER and MSDCITR), the white labeled name for LACI. Information on the index can be found at : https://www.spglobal.com/spdji/en/custom-index-calculations/little-harbor-advisors/all/#overview

I. Introduction

The 60-40 equity-bond allocation rests on the investment strategy that harvests high-yielding stocks in good times, while investment in bonds provides a cushion in bad times. The 60-40 allocation has attracted negative sentiment for several reasons[1]. First, until recently, a near zero-interest-rate environment reduced investor optimism for bonds as they offered low to negative real yields. Next, bonds have not provided the needed diversification benefits due to increased correlation with equities during the last two decades. The fact that both markets respond to some common factors is a widely accepted view in the literature (see Fama and French (1988), Campbell and Ammer (1993), Keim and Stambaugh (1986), Harvey et al. (1994), and Ilmanen (1995). Naturally, if common economic drivers are used to analyze and forecast equity and fixed-income returns, it may lead to correlated trades. This increases the correlation between fixed income and equity markets, precisely what investors do not want in a down market. Finally, a lack of transparency and liquidity in portions of the fixed-income market, especially in the corporate bond market, discourages investors. Naturally, it is not surprising that the 60-40 popular portfolio allocation has recently come under fire. Some asset managers such as Pimco, Goldman Sachs, the Bank of America, Merrill Lynch, and JP Morgan have recently suggested that the 60-40 rule may be 'dead.' or needs tweaking[2].

Commodities have always been viewed favorably for increasing diversification benefits in a standard 60-40 portfolio. The concept gained widespread traction with the introduction in 1991 of the GSCI[3] by Goldman Sachs. It marked a turning point, providing a widely recognized and investable total return benchmark for the commodity asset class. From 1991-2004, primarily sophisticated institutional investors took advantage of this new environment of commodity investment. Since 2004, many new innovative products have made commodities more accessible to a broader group of investors (see Miffre (2015) for a review). In particular, developing these new innovative products responded to several significant changes

[1] Also see, https://seekingalpha.com/article/4336151-end-of-60-40-portfolio-explained
[2] https://www.blackrock.com/us/individual/insights/60-40-portfolios-and-alternatives and https://am.jpmorgan.com/kr/en/asset-management/institutional/insights/market-insights/market-updates/on-the-minds-of-investors/rethinking-the-60-40-portfolio/ and https://www.barrons.com/articles/60-40-portfolio-investing-liquid-alts-funds-51647901871
[3] In 2002 Standard & Poor's became the calculation agent for the Goldman Sachs Commodity Index. The GSCI index became S&P GSCI, or SPGSCI, in 2007.

that have impacted how the commodity markets traditionally functioned. The introduction of the "all-weather" methodology of investing, popularized by Ray Dalio of Bridgewater Associates, has been warmly received by the investing public as a prudent way to achieve stable investment returns with acceptable levels of volatility in all market environments. However, commodity inclusion in all-weather portfolios has suffered from the commodity market's paradigm shift. This change includes increased correlation with other asset classes and the economy, opaque investment strategies, changes in commodity futures forward curve structures, high fees, and a persistent low-yielding fixed-income market environment. The paradigm shift has reduced the critical diversification component of commodities as a key allocation.

This paper develops a liquid alternative commodity index (LACI)[4] to gain smart exposure to the commodity asset class, considering broad economic and political changes affecting commodities markets. Our investment strategy is based on proprietary algorithms and incorporates a long/short monthly positioning and rebalancing methodology. It is a transparent, highly liquid strategy and provides more stable returns than the widely recognized long-only commodity index benchmarks. The proposed investment strategy can deal with systemic exposure of the selected commodity contracts to the economy, broad asset classes, and extract high-quality signals when commodity futures contracts oscillate between contango and backwardation. We also demonstrate that our unique strategy has a high Sharpe ratio, unlike many of its 'close competitors'[5]. To highlight the investment value of the index, we create a balanced portfolio by adding LACI to a portfolio of fixed-income and equity assets. Risk-adjusted performance shows that our strategy generates superior performance compared to most brand-name CTAs, hedge funds, alternative mutual funds, and ETFs.

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[4] Returns from this alternative index shown throughout this paper are NET of expected transaction costs and a .85% implied annualized management fee.

[5] We use the term 'close competitors' loosely because of the difficulty in identifying close substitutes for LACI in terms of size, scope, asset classes, positioning methodology, fees, and strategies. As a result, we will consider both broad indices representing equity, fixed income, currencies, commodities, ETFs, ETN, hedge funds/CTAs, and mutual funds~~., and other CTA products.~~ Such comparisons may not be accurate though our intention is to point out the universe of assets that LACI can interact with.

In Section II, we review the literature on a wide array of commodity programs to motivate the development of our new strategy. Section III presents the performance data with critical comparisons between the LACI and its competitors. The final section concludes the paper.

II. Review of the Literature

Anecdotally, a smart commodities strategy has to effectively deal with paradigm shifts from, for example, rising correlation among major asset classes, high equity valuation, low-interest-rate environment, unprecedented global monetary, fiscal, and political shocks, forward pricing structure, and falling commodity prices[6]. Most prominent among these factors are rising correlations, forward pricing, and order flows associated with periodic rolls. These factors have also shaped most commodities investment strategies attempting to adjust to these paradigm shifts. Unfortunately, as we will report, most of these strategies have yielded mixed results.

Rising Correlations Among Broad Markets

Portfolio diversification rests on negative correlations between assets in a basket. When correlations increase, diversification benefits fall. The correlations among the major asset classes (broad indices[7]) for the period 2000 – 2023 are:

	Stock	Bond	Currency
Bond	-.21		
Currency	-.11	-.19	
Commodities	.28	-.10	-.28

Commodities are positively correlated with the stock and negatively with the bond market and currencies. In contrast, stock, bond, and currency markets are negatively correlated. Given the negative unconditional

[6] There are studies that defend the 60-40 rule. See https://corporate.vanguard.com/content/corporatesite/us/en/corp/articles/like-phoenix-6040-portfolio-will-rise-again.html

[7] Daily returns for January 2000 – June 2023 are calculated using the following assets: Stock (SPDR SPY Trust etf), Bond (Bloomberg Aggregate Bond Index - LBUUSTRU), Currencies (inverse of the dollar index (DXY), and S&P-Goldman Sachs passive long-only commodities index (SPGSCITR).

correlation, the 60-40 stock-bond portfolio allocation should be effective. Unfortunately, unconditional correlation (average correlation) does not capture the dynamic evolution of correlations over time and how it affects asset allocation. Connolly et al. (2005) show that the correlation of daily stock and bond yield varies over time. We also estimate the time-varying correlation among broad asset classes using a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH[8]) model. This is also in response to the preliminary evidence that asset returns are distributed with autocorrelation, volatility clustering, time-varying variances, and covariance. In essence, returns are not normal. Our model produces six bilateral correlations oscillating between positive and negative values over time.

Figure 1 reports time-varying correlations among stock, bond, currency, and commodities indices over time (2000-2023). It is evident that the six bilateral correlations are unstable and change with time. Note that the stock-bond-commodities correlation has oscillated between positive and negative values, suggesting that a passive long-only commodity strategy may not be suitable for diversification. Over time, correlations have drifted among the major asset classes, sometimes even changing signs. Notably, the stock-bond correlation has changed positively and negatively over time. This correlation has recently turned positive, signifying decreased diversification benefits in a 60-40 portfolio. Even more striking is that adding passive long-only commodities positions fails to deliver the much-needed diversification investors demand in times of stress. It has failed because passive long-only positioning cannot deal with market dynamics and the cyclicality of the relationship among the major asset classes. As the correlation diagram reveals, what is needed is an active long-short strategy as the relationship waxes and wanes.

Despite the increasing correlations among the key asset classes, allocations to commodity-based hedge funds and managed futures as alternatives to core fixed-income exposures (see Figures 2 and 3) continued. Over the years, this increasing allocation to alternative investment vehicles has contributed to the growth of the altered state of commodity markets. The main consequence of these asset flows has been partly responsible for the increased correlation between SPGSCITR and a broad-based equity market index

[8]The time varying correlations are estimated using bivariate GARCH models, same as the one reported in Kroner and Sultan (1992). The methodology is quite standard and is reported in Appendix A.

like the S&P500. We suspect this is a consequence of factor crowding, where investors use the same systemic factors to trade the same basket of stocks or commodities. Factor crowding increases herding among investors, increasing the correlation between markets[9]. Passive long-only commodity market investing has increasingly correlated with broad stock and bond indices, thus eroding diversification benefits. Including a long-only commodity exposure in a well-diversified portfolio faces strong headwinds from a rising correlation between equities, bonds, and commodities. This is counter to what most academic work before 2005 indicated should be the case. These papers argued that "high real commodity prices can be a signal that monetary policy is loose" (Frankel, 2006). This has not been the case during the recent extended period of accommodative Fed policy. This has typically resolved as the business cycle plays out and the traditional correlation relationships re-establish themselves.

Has the commodity market permanently changed? If so, what part can be attributed to the considerable amount of passive investor funds[10] contributing to the diminished return expectations from a long-only exposure to commodities? The previous table suggests that an investor's ability to utilize commodities as a diversifying investment now requires a more active approach like those used by hedge funds, alternative fund of funds, and CTAs. Historically, managed futures have proven to be a valuable diversifier to a traditional equity/bond portfolio; however, their lack of transparency, high fee structure, manager selection, and style drift issues have kept many investors from utilizing these strategies. Overall, the search for yield has continued to siphon AUM towards alternatives (see Figures 2-3).

Forward Pricing

Large pools of long-only funds have also affected the way forward markets in many key commodity futures functions. Most commodity allocations and benchmarks are heavily weighted towards the energy sector, specifically WTI Crude Oil. Through 2004, Crude Oil futures were primarily backwardated, a pricing

[9] Factor crowding refers to hedge funds following similar systemic factors to forecast equity risk premium. As a result, these hedge funds strategies are becoming more correlated, leading their risk premiums to be arbitraged away. See Cahan (2013) for more.
[10] Since 2004, commodity futures open interest has more than doubled.

structure that allowed a passive investor to maintain a long position by rolling from a higher-priced futures contract into a lower-priced one with the expectation of capturing a “roll yield”[11]. The Crude Oil market went from a pricing structure dominated by a backwardated curve structure to being dominated by a contango curve structure since 2005. This pricing anomaly had been a primary driver of returns for Crude Oil and commodities (Erb and Harvey (2005)). This new forward structure has resulted in changing what was once a “roll yield” into a “roll cost” (Bhardwaj, Gorton, Gary, and Rouwenhorst (2015)). Figures 4 and 5 demonstrate the futures curve for WTI Crude Oil on 10/1/1997 and 11/30/2015. As can be seen (Figure 6), the WTI crude oil market has historically oscillated between contango and backwardation. Between 1989 and 2004, WTI spread traded 68% of the time in backwardation. Since 2005, the WTI has traded in contango 65% of the time.

Periodic Rolls

There have been noticeable increases in large order flows ahead of periodic rolls by major commodity hedge funds and index providers. Trading ahead of the major rolls is primarily devoted to avoiding the negative effect on spreads when index providers roll from the front month to the next nearby contracts. In Figure 7 we can see the changes to the WTI Crude Oil futures market in the forward curve and the changing dynamics of the WTI Crude Oil roll period associated with the SPGSCITR. Each index component commodity, when required, is rolled forward during the month's 5th through 9th business day (shaded area). Other long-only commodity index benchmarks also roll early in the month on varying time frames, similar to the SPGSCITR methodology. As can be seen, the early part of the month through 2004 had marginal roll costs compared to the significant slippage associated with the roll function since then. Although the roll of month 2 to month 3 is shown, a similar analysis demonstrates this degrading roll yield function across the active 12-month forward curve. Fama and French (1987) cite interest rates and

[11] In a backwardated market, the inventory is low and the benefits of owning the commodity for selling in future exceeds the cost of storage. So, the futures price rolls up to the expected spot, generating a positive roll-yield for those going long. In a contangoed market, storage costs exceed the roll yield as the futures price gravitates downward to the spot market. In a contangoed market, short positions capture the negative roll-yield.

convenience yield to affect the roll yield or the basis. Gorton, Hayashi, and Rouwenhorst (2012) claim that inventory is the principal driver of the basis.

Commodities Investment Strategies Responding to Paradigm Shifts

In response to the paradigm shifts, commodity-specific offerings have been plentiful. However, they have mainly focused on providing non-futures-based exposures to the retail investor class through exchange-traded funds (ETF), exchange-traded notes (ETN), and mutual funds. Many are single commodity-focused investments, such as gold or crude oil. Index-based commodity products involve standard index-tracking vehicles that mimic popular long-only commodity indices and more innovative structures. These alternative structures rely on strategic methodologies that provide a long-only exposure but seek to increase returns using trading strategies such as alternative roll methodologies versus those used by index providers.

Investors can choose from this broad array of strategies in more cost-efficient structures such as smart beta indices that various firms have introduced. A survey conducted by FTSE Russell states that "out of 178 retirement plans, endowments, foundations, and other institutions polled by the index provider, 58 percent said they had allocations to smart beta strategies, up from 48 percent last year. Another 20 percent said they were evaluating or planning to add smart beta to their portfolios".[7] While most of these are equity products, there have been a few in the managed futures space and, to a lesser degree, commodity-specific offerings. Commodity-based smart beta products utilize various strategies, including long/short positioning, inter-market spread trading, contango/backwardation-based analysis, and trend following. The managed futures smart beta products attempt to provide index-type vehicles that give investors the returns from a broad array of managers in various futures-based investment strategies but with more transparency, higher liquidity, and more competitive fee structures. These strategies cover equities, fixed income, currencies, and commodities. One of the earlier and more recognized managed futures products is AQR Managed Futures Strategy Fund (AQMIX), with $1.4 billion AUM, down from $6 billion only a few years ago. Since its inception in 2010, the fund has produced 2.757% annualized return, with a 0.18 Sharpe ratio[12].

[12] "Most Asset Owners Are Now Smart Beta Investors", Institutional Investor June 2019

The roll yield has been used as a signal in trading strategies (Erb and Harvey (2006), Dewally, Ederington, and Fernando (2013), and Gorton et al. (2012). In a backwardated market, a high roll yield suggests going long; in a contango market, a high negative roll cost suggests that going short would be profitable. These studies also suggest that the long-short portfolios trading the roll-yield generate returns similar to long-only passive commodity indexes like the S&P/Goldman Sachs Commodity Index (ticker: SPGSCITR- based on data before 2004). In contrast, studies found profitable trading strategies based on standardized inventory (defined as inventory divided by the 12-month moving average inventory)[13]. According to Gorton et al. (2012), profits from inventory-based trading strategies have higher returns for commodities with backwardated futures curves. Inventory-based long-short strategies have a Sharpe ratio of .46 compared to long-only portfolios rebalanced at monthly frequencies.

Are the returns from backwardated markets different than contagoed markets? The hedging pressure hypothesis (see Herschleifer, 1988), which derives its root from the normal backwardation theory (Keynes, 1930), states that net short hedgers face a risk of falling prices offer a risk premium to net long speculators. As futures price is expected to rise around expiry, long-run speculators earn a positive risk premium[14]. So, backwardated and contangoed markets are driven by hedging pressure. Several researchers have provided empirical support (see Bessembinder (1992) and Basu and Miffre (2013) and references therein). Basu and Miffre (2013) developed a long-short strategy based on 27 commodity futures and generated an average Sharpe ratio of 0.51 for 1992-2011. This contrasts with a Sharpe ratio of 0.08 from a long-only equally-weighted portfolio that includes all commodities for the same period. During the same period, the SPGSCITR generated a Sharpe ratio of 0.19. These findings have been challenged (Daskalaki, Kostakis, and Skiadopoulos (2014)). They show that returns to net short hedgers in a backwardated market are statistically insignificant compared to those earned by net long hedgers in a contagoed market.[15]

[13] The ratio is lower in a backwardated market.
[14] Similarly, the futures price needs to be set at a high level for net short speculators to accommodate hedgers who are net long.
[15] See Miffre (2015) for an analysis of the differences between these studies that may explain different results.

Long-short trend-following strategies (Erb and Harvey (2006) and Blitz and De Groot (2014), to name a few) applied to the commodity futures markets are popular and have done well in the past. The trend-following momentum studies are of two types: cross-sectional and time-series momentum. Both strategies have done well (see Miffre (2015) for a summary). Generally, the cross-sectional momentum strategy that buys the winners and sells the losers has a Sharpe ratio of 0.50, in contrast to -0.24 Sharpe for a long-only equally weighted portfolio (Miffre and Rallis (2007)).

While the cross-sectional momentum strategy is the most popular, the time-series momentum strategy has also performed well. According to a study by Szakmary, Shen, and Sharma (2010), this strategy has a Sharpe ratio of 0.52. Hurst, Oci, and Pedersen (2014) of AQR Capital Management offer a strategy with a Sharpe ratio of 0.77, net of all fees, for January 1983 – December 2013. The authors attribute several factors contributing to this strategy's success, including investors' behavioral biases, market frictions, hedging demands, and market interventions by regulatory bodies such as the central banks and governments.

Studies on trend following long-short strategies based on various measures of risk such as beta, total risk, and idiosyncratic volatility exist (see Frazini and Pedersen (2014), Gorton, Hayashi, and Rouwenhorst (2012), and Szymanowska, De Roon, Nijman, and Van Den Goorbergh (2014)). The beta-based strategy (Frazzini and Pedersen (2014)), which involves buying low-beta assets and shorting high-beta assets, has a Sharpe ratio of only 0.11. Gorton, Hayashi, and Rouwenhorst (2012) note that a high-volatility portfolio statistically outperforms a low-volatility portfolio by 5.41% annually. Regarding the Sharpe ratio, the long-short portfolio compares favorably to a long-only portfolio. Fernandez-Perez, Fuertes, and Miffre (2015) use residuals from a model that includes roll yields, hedging pressure, and past performance to form quantile portfolios of commodities futures. The strategy (long contracts with previous high performance, high roll-yields, and low idiosyncratic volatility and short contracts with previous low performance, low roll-yields, and high idiosyncratic volatility) has a Sharpe ratio of 0.38, which is higher than 0.02 Sharpe ratio of the SPGSCITR (for the same time frame).

Finally, there are other strategies, including cheapness/dearness, liquidity, inflation beta, dollar beta, open interest, skewness (long contracts with the most negative skewness and short contracts with the most positive skewness), and the term structure of the commodity contracts (for example, shorting nearby contracts and buying distant contracts). Some of these strategies have produced attractive returns compared to their chosen benchmarks. See Miffre (2015) for a review.

Overall, the trend following long-term strategies using commodity contracts duplicates popular stock investing models. To the extent that investment psychology differs between the markets, it is unclear that some models can deal with contango and backwardation features in the commodity markets. Also, the stock market's exposure to the world's geopolitical environment differs from the commodity markets' exposure. Still, it would be interesting to experiment with the three or five-factor Fama-French model to examine the performance of our proprietary index. As noted earlier, the flow of AUM into passive long-only portfolios has exacerbated the correlation between commodity and stock indices. The models have performed well in the past. However, their recent performance raises the question of whether improvements can be made by developing alternative strategies robust to the paradigm shift in the commodity markets.

III. All-Weather Liquid Alternative Commodity Index (LACI)

Data

Our all-weather active commodity index is based on daily data on 23 commodity futures contracts representing most of the commodities included in the SPGSCI and S&P Dow Jones Commodity Index (SPDJCI)[16]. We also collect data on conventional assets such as stocks, bonds, currencies, and several ETFs and mutual funds representing commodity strategies that can be considered somewhat related (but not identical) to our proposed index. The data covers January 2000 to June 2023, and data on relevant indices and other comparable assets are available at irregular intervals. Data are collected from Bloomberg terminal, Yahoo finance, and Barchart.com and we adjust the futures data for periodic roll to the next nearby liquid contract. Data on listed equity and commodity products are end-of-day prices. Because of data availability, some analyses were performed using different sample periods. We also construct two other versions of the

[16] Currently, the SPGSCI and SPDJCI have 28 commodities. The reason we do not use 24 commodities is we exclude non-U.S. Exchange listed contracts.

principal strategy that offer targeted diversification benefits when included in traditional portfolios. Regressions models are estimated using SAS, adjusted for nonlinearity in the returns distribution.

LACI Methodology

As noted, previous attempts to use commodities as *passive* diversifiers suffer from paradigm shifts due to, for instance, contango-backwardation oscillation, herding, and time-varying correlations among major asset classes. What is needed is a commodity index that incorporates an investment strategy that allows investors to pursue an active commodity strategy. Unlike most long-only or short-only passive investment styles, the commodity index should be based on fixed algorithms and incorporate a long/short fully invested positioning methodology. The proposed investment strategy should minimize the costs associated with timely rebalancing systemic exposure of the commodity contracts to the equity and bond markets, and extracting high-quality signals when commodities futures contracts oscillate between contango and backwardation. The risk-adjusted performance (net of expected transaction costs and management fees) should demonstrate if the strategy is superior to most brand-name commodity trading advisors (CTAs), hedge funds, alternative mutual funds, and ETFs. Our strategy meets or exceeds these constraints. The proposed investment strategy, which we refer to as the Liquid Alternative Commodity Index (LACI), stands out among many competing indices and investment strategies. In addition, the strategy considers the disparate signals identified in the literature, such as backwardation, contango, roll-yields, momentums, cheapness/dearness, idiosyncratic volatility, beta, and hedging pressure[17].

Attribution Analysis

We conducted an attribution analysis to break down our trading strategy's performance, separated into five sample periods: January 2000 – December 2004, January 2005 – December 2009, January 2010 – December 2014, January 2015 – December 2019, and January 2020 - June 2023 (full sample). These are

[17] Because of the S&P validated proprietary nature of the index, the exact methodology, weights, and position determination algorithm will not be disclosed.

arbitrary sample periods broadly coinciding with several global financial and geopolitical events[18]. We aim to decompose returns and volatilities across these regimes granularly to show that our all-weather investment strategy performs in all environments.

Some of the salient features of the return decomposition of LACI are noted in Table 1. In Panel A, the average annual return on LACI peaked at 24.42% during the financial crisis, albeit with correspondingly high volatility. The post-financial LACI returns were on a downward trend, while volatility remains at 13.16%, which is high. Panel A also shows the percentage of LACI returns contributed by individual commodities. Again, the energy sector remains the principal contributor. For example, during 2005-2009, as much as 35% of the LACI returns were generated by WTI Crude Oil (we were short crude during this period). It is not unusual for the energy sector to drive returns for any broad commodity product.

Interestingly, few competing alternative commodity long/short programs have a rule that they cannot short crude oil due to geopolitical concerns. Oil can spike upwards because of such exposure. Increased U.S. energy independence has mitigated this concern to a great extent. Many investment programs have also missed the change from backwardation to contango, with a significant roll yield coming from the energy space. As for Natural Gas, those returns were from the clear trends created due to the price spike in 2000 and the Amaranth hedge fund collapse in late 2006. These events created artificial bubbles in Natural Gas, allowing the program to identify and ride these positions for large profits. Over the remaining sample periods, major contributors to LACI returns were Natural Gas, WTI Crude Oil, and HG Copper.

[18] For example, the period 2000-2004 was the longest bull market in the U.S., preceding the subprime crisis. This was when several major bullish trends in commodities were recorded as investors squarely embraced the notion of commodities in investment decisions. Commodities were injected into traditional investment portfolios, from the run-up of oil markets to natural gas. The 2005 – 2009 period coincided with the financial crisis due to subprime problems. The period 2010 – 2014 included several significant economic and political events, including Grexit, the global equity market recovery coinciding with record-low interest rates and inflation, the European sovereign debt crisis, and the 2014 Russian-Ukraine war. The period 2015-2019 saw two major events – the Brexit and the U.S. Presidential election leading to a double-digit rise in the stock market. Finally, the period 2020 – 2023 saw the pandemic, commodity price deflation, and the Russian-Ukraine war. The period also coincided with the major equity market uncertainty reflecting concerns about budget crises, contentious presidential election in the U.S., the recovery from the COVID-19 pandemic, heightened monetary policy uncertainty and a 30-yr high inflation that dealt a devastating blow to global equity, fixed income, and the commodities markets. While commodities recovered from their slump in early 2020 to the peak in January 2022, since then, commodities fell by as much as 14 percent, reflecting slowing economic activity and good crop weather. The sharpest decline in commodity prices since the pandemic and is expected to continue further in 2024 (World Bank Commodity Outlook, 2023).

Volatility decomposition tells an interesting story. Crude oil was the most significant contributor to the volatility of LACI for all sample periods. Conversely, Gold and HG Copper were responsible for most declines in LACI. Among the remaining lowest contributors to the LACI's volatility were Feeder Cattle and Platinum.

Panel B, Table 1, reports average aggregate positions by %long and %short. Notice that %long positions peaked during the financial crisis but have declined since. Interestingly, %short rose during the 2015 to 2023 period. Half the time, maximum long positions pertain to Platinum. In contrast, non-energy components are among the commodities with maximum short positions for the sample periods. Minimum long and short positions for the 5 sample periods are also shown in Panel B, and it is impossible to draw any definite conclusion. Long-short positions in any commodity do not persist across sample periods. This reflects the possibility that LACI is a dynamic strategy that adjusts its commodity positions in response to changing market conditions.

We report the performance of LACI against 21 comparable listed commodity strategies in Panel C, Table 1. As noted in footnote 5, while we identify these programs as 'close competitors', this classification is arbitrary because they are quite different from LACI regarding style, size, methodology, member constituents, and sample periods. Nevertheless, we highlight a few salient performance data. Regarding maximum drawdown, LACI has the lowest number at -23.31%, while iShares S&P GSCI Commodity-Indexed Trust (GSG) and iPath Bloomberg Commodity Index Total Return (DJP) have the highest drawdown at -88.68% and -77.3%, respectively. LACI also has the highest Sharpe ratio among the 23 assets in the table. It also generated 7.92% return since inception. The Sharpe ratio indicates that LACI beats all its competitors[19].

Comparative Performance of LACI

As noted earlier, LACI is simple, innovative, transparent, and rules-based index and uses trends to establish long-short positions. It trades once at the beginning of the month and keeps these positions fixed.

[19] To save space, we report a few selected performance statistics of LACI in Table 1. Complete performance results are available upon request.

Figure 8 plots our strategy (LACI) against several arbitrary investible benchmarks, including the SPDR (SPY), SPGSCITR, Bloomberg Commodity Index (BCOMTR), and Vanguard Total Bond Market Index (VMMFX). Our strategy generates superior performance compared to the benchmarks. It has an adjusted Sharpe ratio of .43 for the entire sample[20], which compares quite favorably against the benchmarks. Historically, the strategy fares quite well in dealing with major economic and political events. Table 2 lists 12 major events since 2000 and our strategy's performance compared to returns from equity (total returns index from the SPY and managed futures (as represented by the Société General CTA Index (NEIXCTA)) around these event dates. LACI offers higher returns on a relative basis than the returns on SPY and the managed futures (NEIXCTA). All in all, LACI beats total returns on S&P500 by +345.95% (=143.59% - (-202.36%)) during these key events. LACI offers +199.02% (=143.59% – (-55.43%)) higher returns than these managed futures. Compared to SPGSCITR, LACI offers 267.96% higher returns (=143.50%-(-124.37%)). The highlight of LACI's performance can be illustrated with the fact that it performed well when the equity market fell. For example, during the financial crisis, the S&P fell 46.32% while LACI increased by 74.95%. This is not an isolated incident as Table 2 shows LACI performing well when the equity markets decline. Compared to the popular commodity benchmark, SPGSCI, LACI demonstrated its resilience quite well.

Aggregate Correlations Among Broad Indices and Selected Assets

It is our belief that the popular 60-40 allocation has suffered due to rising correlations among broader classes of assets. As Figure 1 reported earlier, markets are increasingly correlated, confirming our hypothesis of paradigm shifts in the market. Therefore, we include 11 popular indices representing stocks, bonds, currencies, and commodities for our analysis and show how LACI relates to these broad sectors.

Correlations between LACI and selected assets are shown in Table 3. There are broad asset pairs that are correlated because they represent similar industries, such as REITs (index of real estate stocks) and MBS (mortgage backed securities). LACI is uncorrelated with many of the assets selected in the sample. During 2000-2023, LACI has the following correlations: -.15 (SPY), .035 (Bond), .02 (Muni), .08 (US

[20] We adjust the Sharpe ratio for serial correlation. See Rulle (2015) for more.

Treasury), -.11 ((index of high-yield corporate bonds:High Yield), .01 (MBS), -.11 (REITS), -.013 (Currency:DXY), and -.08 (Commodities:SPGSCI). Compared to that, commodities (SPGSCI) has positive correlations with the majority of the assets, except Bond, Muni, US Treasury, and MBS.

For the remaining subsamples, LACI's relationship with key indices remained stable and the correlations did not change signs. For the period 2000-2004, LACI was negatively correlated with SPY and REITS. It was positively correlated with the remaining indices. In contrast, SPGSCI was negatively correlated in five out of eight assets, demonstrating that commodities were effective for risk mitigation during this period. For the 2005-2009, LACI was negatively correlated in five out of nine instances, while SPGSCI recorded a positive correlation with SPY, High Yield, REITS, and currency. During 2010-2014, correlation of LACI was negative in five instances and positive correlation in four instances. Compared to that, SPGSCI was positively correlated in four out eight cases, with the largest correlation noticed with SPY. Clearly, during this period, long-only commodities strategy did not provide investors the needed diversification. For the 2015-2019 (pre-COVID sample), LACI was negatively correlated in four out of 9 cases, while SPGSCI was negatively correlated four out of eight cases. During the COVID pandemic, we see an interesting pattern for LACI correlation (Panel D). The correlation of LACI with major indices (equity, bond, high yield, MBS, REITS, and SPGSCI) was negative. For Muni, US Treasury, and currency, LACI's correlation was positive. During the period, SPGSCI was negatively correlated in two out of eight cases suggesting that commodities did not provide the needed diversification as effectively as LACI.

Overall, Table 3 indicates that the correlation fluctuated a lot among the major market indices, exactly as shown in Figure 1, though LACI remained consistently. Some of the subsamples are too short to draw any definite conclusion regarding how correlations have behaved in that period. For the remainder of the paper, we will concentrate on the full sample (2000-2023) to analyze the effectiveness of LACI compared to SPGSCI and other competing assets.

Exposure to Broad Markets

The correlation coefficients reported in Table 3 show that the relationship among the asset classes has varied as markets have undergone fundamental changes due to economic, political, and social crises. This section estimates regression models to determine the statistical significance of these correlations, which may be coincidental. We include 46 LACI-like assets[21] with possible commodities exposure. Furthermore, as reported earlier, trend-following long-short strategies using commodity contracts duplicate stock market investing models. Naturally, these alternative and close substitutes of LACI will have exposure to the broad market indices.

Preliminary analysis suggested that LACI and competing asset returns are not normally distributed. Therefore, we estimated a generalized autoregressive conditional heteroskedasticity (GARCH) model. The model assumes changing distributions of the second moments of the returns with volatility clustering. The model is:

$$R_t = \delta_0 + \delta_1 SPY_t + \delta_2 Bond_t + \delta_3 US\,Treasury_t + \delta_4 DXY_t + \delta_5 SPGSCI_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t | \psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \tag{2}$$

$$\sigma_t^2 = \Omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j} \tag{3}$$

where R_t in the mean equation (equation 1) is the daily return for a particular asset under attention. Equation (2) describes the returns distribution with time-varying conditional variances (Ψt-1 is the information set). The variance equation (3) models the conditional variances as a GARCH(p,q) process where p and q denote the lag length. Ω is the intercept term, αi are ARCH terms, and βj are GARCH terms. We would expect α

[21] We include the following assets (indices, funds, and ETFs): SPDR (SPY), Barclays bond index (Bond), DXY (US dollar index), and SPGSCI. We have also included the following ETFs, mutual funds, and ETNs (ABYIX, AHLIX, AMFNX, AQMRX, ASFYX, BCD, BCI, BCSAX, BCSKX, BRCAX, CCOMX, CCRSX, CCSRX, CMCAX, CMDY, COM, COMT, CRSAX, DBC, DBMF, DJP, EVOIX, FCSSX, FIFGX, GAAVX, GCC, GFIRX, GLD, GSG, JCCSX, LACI, LCSIX, LFMIX, LOTIX, MCSAX, PCLPX, PCRAX, PCRPX, PDBC, PQTIX, PZRMX, QMHRX, RJI, SKIRX, SLV, VCMDX, and WTMF).

and β terms to be positive and significant determinants of the conditional variance. The model is estimated assuming t-distribution for the error term[22].

The independent variables are chosen assuming that commodities strategies compete with stocks, bonds, US Treasury, and currencies for investment flows over specific times. Our focus is on the sign and significance of the relationship between commodities strategies and broad market indices. A positive and significant sign for the coefficient would imply positive exposure which also reduces the diversification benefit for including both assets in a portfolio, while a negative relationship would imply the opposite. The results[23] for the full sample (2000-2023) are reported in Table 4. In 16 out of 47 cases, the estimated intercept term is positive and significant. The highest intercept is noticed for the asset AMFNX (Virtus AlphaSimplex Mgd Futures Strategy R6 (AMFNX) which is a 2.27b absolute return strategy investing in fixed-income, currency, equity, and commodity derivatives. The fund, which identifies systematic trends using quantitative models, is rated four star out of five in Morningstar. The lowest intercept term was noticed for BCSAX (BlackRock Commodity Strategies) which is a $713m product rated three star by Morningstar. For 5 cases, the relationship is negative and significant.

Moving on to benchmark-level exposure of the selected assets, we find that in 31 instances, the coefficient on SPY is positive and significant at least at the 10% significance level. Compared to that, five instances of the effects of SPY are significant and negative. The commodity strategy with the highest positive coefficient on SPY is BCSAX and the lowest negative coefficient is noticed for QMHRX (AQR Managed Futures Strategy HV Fund), which is a $150.66 fund. For the bond market, SLV (IShare Silver Trust) a $10.13 bill fund has the highest positive coefficient and the strategy with the largest negative coefficient for Bond is DBMF ETF (iMGP DBi Managed Futures Streategy). For the currency market, in 17 instances a dollar appreciation leads to an increase in the returns of the selected funds. In 29 cases, an appreciation of the dollar is associated with a negative return on the assets selected. ABYIX (a $2.6b Abbey Capital Futures

[22] The GARCH model also estimates TDFI which is the inverse of degrees of freedom parameter and the associated t-statistics. Suppose the estimated parameter is 0.23. This would imply that the normality assumption is not valid as the degrees of freedom is 4.35 (=1/.23). The assumption of t-distribution corrects for the low degrees of freedom.

[23] To save space, we will only report the results for the full sample. Complete results for the remaining subsamples are available upon request.

Strategy), four star rated strategy has the largest positive coefficient. Compared to that, SLV has the smallest largest negative coefficient. The effects of commodity benchmark (SPGSCI) are mostly positive. In 40 instances the coefficient is positive and significant and in 4 cases the coefficient is negative and significant. The asset with the largest positive coefficient is GSG ($941.96m iShares S&P GSCI Commodity-Indexed Trust), and QMHRX has the largest negative coefficient on SPGSCI. Finally, LACI has insignificant intercept for the full sample. It is also affected negatively by increases in SPY and DXY and positively by SPGSCI. A negative relationship with the equity and the currency market offers evidence of diversification benefit of including LACI, equity, and the currency market in a portfolio. A positive relationship with the commodities market assures that LACI participates in a rising commodities market.

Overall, the GARCH models offer a more convincing cause-effect relationship between LACI and selected broader markets. In addition, residual diagnostics of the models reveal that they provide a parsimonious representation of the return distributions of these assets.

Fama-French Factor Model

The trend-following long-short strategies using commodity futures contracts correlate to broad market indices. So, the regression-based confirmation of the correlation reported in Table 4 earlier is important as we can be sure of the cause-effect relationship without rigorous theoretical models. However, these regression models do not offer convincing proof of performance. Therefore, we need to estimate popular stock investing models like the Capital Asset Pricing Model (CAPM) or Fama-French five-factor model. However, to the extent that investment psychology differs between the markets, it is not clear that some of these factor models can deal with contango and backwardation features in the commodity markets. Also, the stock market's exposure to the world's geopolitical environment is different from the commodity markets' exposure. Nevertheless, it would be interesting to experiment using the CAPM or Fama-French factor model if our proprietary index has exposure to the equity market.

The Fama-French model[24] proposes efficient security pricing by combining risk-free and possible investment portfolios in a mean-variance efficient tangency framework. Its sole purpose is to explain cross-sectional variation in expected returns. While the single factor model performed well until 1993, Fama and French added additional factors to improve the model's forecasting power[25]. The authors write:

> "A five-factor model directed at capturing the size, value, profitability, and investment patterns in average stock returns performs better than the three-factor model of Fama and French (FF 1993). The five-factor model's main problem is its failure to capture the low average returns on small stocks whose returns behave like those of firms that invest a lot despite low profitability. The model's performance is not sensitive to the way its factors are defined. With the addition of profitability and investment factors, the value factor of the FF three-factor model becomes redundant for describing average returns in the sample we examine." (Fama and French, 2015).

The Fama-French factors are (adapted from Ken French's website[26]). Mkt_rf is the value-weighted excess return on the market of all firms included in CRSP, rf_t is the one-month Treasury bill rate (from Ibbotson Associates), SMB (Small Minus Big) is the average return on the small stock portfolios minus the average return on the big stock portfolios, and HML (High Minus Low) is the average return on the value portfolios minus the average return on the growth portfolios. This is the three-factor model. By adding two additional factors, we have a five-factor model. These additional factors are: RMW (Robust Minus Weak) is the average return on the robust operating profitability portfolios minus the average return on the weak operating profitability portfolios and CMA (Conservative Minus Aggressive (firms that invest aggressively)) is the average return on the conservative investment portfolios minus the average return on the aggressive investment portfolios. Conservative represents firms that invest conservatively.

As reported earlier, trend-following long-short strategies using commodity contracts duplicate stock market investing models. Naturally, these alternative and close substitutes of LACI will have exposure to the

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[24] We estimated a single factor CAPM and also three-factor Fama-French models. While simple is better, we want to be consistent with a vast majority of the literature and opt for the five-factor Fama-French model.
25 The authors also note that by adding profitability and investment factors, the HML becomes redundant.
[26] The description of the Fama-French factors is adapted from the Ken French's website. We modified the adaptation slightly. We recommend interested readers to the seminal Fama and French, 1993 article, "Common Risk Factors in the Returns on Stocks and Bonds," Journal of Financial Economics, and the Fama and French, 2014, "A Five-Factor Asset Pricing Model" for more on why the 5 factor model is an improvement over a single factor CAPM model. Also see AQR, 2014. Our Model Goes to Six and Saves Value From Redundancy Along the Way. [online] Available at: https://www.aqr.com/cliffs-perspective/our-model-goes-to-six-and-saves-value-from-redundancy-along-the-way for additional discussions.

Fama-French five-factor model. We estimate a Fama-French five-factor model for a selected number of assets to evaluate their exposure. Because LACI and competing asset returns are not normally distributed, we estimated a generalized autoregressive conditional heteroskedasticity (GARCH) model. The model assumes changing distributions of the second moments of the returns with volatility clustering. The model is:

$$R_t = \delta_0 + \delta_1 Mkt\_rf_t + \delta_2 SMB_t + \delta_3 HML_t + \delta_4 RMW_t + \delta_5 CMA_t + \delta_6 RMW_t + \varepsilon_t \quad (4)$$

$$\varepsilon_t | \psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \quad (5)$$

$$\sigma_t^2 = \Omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j} \quad (6)$$

where R_t in the mean equation (equation 4) is the daily return for a particular asset under attention. Fama-French factors are already defined. δ_1 .. δ_6 are factor betas. The model is estimated assuming t-distribution for the error term.

Most equity-like assets should have exposure to the five factors because these factors are based on the aggregate equity market (all screened stocks from NYSE, NASDAQ, and AMEX). However, we want to examine whether commodities-based investment vehicles correlate with the Fama-French factors. The results are reported in Table 5. For the full sample (2000-2023), in 20 instances the assets had a positive alpha, significant at least at the 10% confidence level. Among these assets, the alpha for AMFNX has the largest positive signed coefficient. BCSAX has the largest negative intercept. In contrast, four assets had a negative alpha, significant at the 1% level. **The positive and significant alpha (.021) for LACI offers convincing support for the notion that in addition to being a diversifier, LACI also offers 5.29% annualized pure excess return.** This finding should attract investors searching for commodities investment strategies that offer attractive returns after controlling for all known risk premium factors. It is truly an excess return with all usual caveats applied.

Table 5 Panel also shows that 45 assets had positive exposure to the market risk premium. SPGSCI's exposure to the market risk premium is positive. In contrast, six assets (including LACI) had a negative exposure to the market risk premium. Concerning the remaining factors, as many as eight assets have positive and significant coefficients for SMB (small minus big), suggesting that these assets are weighted towards small-cap stocks. In contrast, 11 assets have significant negative coefficients for SMB. Similarly, 32 assets have positive coefficients for HML (high minus low book-to-market value), suggesting their excess returns are due to value stocks. In contrast, 18 assets' have negative coefficients suggesting excess returns are due to growth stocks. We note that LACI has no exposure to the size and value premium, confirming that the excess returns are primarily due to innovative investment strategies. The coefficient for RMW (the difference between robust and weak profitability) is positive for five assets and negative for 37 assets. The coefficient for investment factor (CMA), the difference between low and high investment firms, is positive for 47 instances. Finally, all ARCH, GARCH, and TDFI coefficients are positive and significant at the 1% confidence level. The estimates for TDFI confirm that the returns are not conditional normal. Therefore, the choice of t-distributed errors for hypothesis testing is appropriate.

The Fama-French results support that LACI offers an innovative solution to many issues that have hindered portfolio diversification using commodities because of correlation and other stylized facts. Since investment psychology differs across assets considered in this paper, we are not confident that these assets can deal constructively with contango and backwardation features in the commodity markets. Also, commodities have different sensitivity to the world's geopolitical environment than stock, bond, and currencies. Still, results from the five-factor Fama-French model suggest that LACI is uniquely positioned to offer performance and diversification to asset managers.

Test of Robustness: Replication of LACI – A Cointegration Analysis

As discussed earlier, LACI's innovative design strongly argues for its inclusion in a well-structured broad portfolio as a critical diversification allocation. How likely can LACI-type returns be harvested by investing in close substitutes? One way to demonstrate this is by testing whether LACI is cointegrated with any of its competitors. Cointegration between two-time series is consistent with short-run deviations of these assets from one another. However, their prices must track each other in the long run as successful arbitrage can push their prices to return to long-run no-arbitrage equilibrium. In other words, if two related variables move together in the long run because they share a common trend, there exists an error correction representation of the common relationship. This implies that today's relationship between these two assets depends on the disequilibrium in the previous period. For related financial assets, cointegration is consistent with the notion of the no-arbitrage condition. This is consistent with Fama (1991), who defines efficiency as a lack of arbitrage opportunities. For instance, Hogan, Kroner, and Sultan (1993) show that the cointegration between the S&P500 cash price and the S&P500 futures price is due to index arbitrage.

The augmented Dickey-Fuller (ADF) tests for cointegration test is carried out in two stages. In the first stage, we check if the prices of pair of assets are nonstationary in the levels individually. If it is determined that they are non-stationary in the level, then we estimate a simple regression to determine if the residuals are stationary. An affirmative answer would suggest that a linear combination of two fundamentally linked assets with individual statistical properties share a long-run relationship. Once they are determined to be cointegrated, we can safely state that one of the assets can be used to replicate the performance of the second asset in the long run.

To check if LACI and SPGSCI are cointegrated. This involves estimating the following single regressions:

$$ln\Delta V_t = \lambda_0 + \lambda_1 Trend + \lambda_2 lnV_{t-1} + \lambda_3 \Delta lnV_{t-1} + \lambda_4 \Delta lnV_{t-2} + \varepsilon_v \tag{7}$$

$$ln\Delta P_t = \alpha_0 + \alpha_1 Trend + \alpha_2 lnP_{t-1} + \alpha_3 \Delta lnP_{t-1} + \alpha_4 \Delta lnP_{t-2} + \varepsilon_p \tag{8}$$

where V denotes LACI and P refers to SPGSCI daily prices, respectively, ln is the natural logarithm operator, and Δ is the first difference operator. If the absolute value of the t-statistic for λ_2 ($\alpha 2$) is less than 3.45 (critical value at the 1% level), then V_t (P_t) is non-stationary in the levels. Once non-stationarity (unit root) is confirmed, the next test examines whether a linear combination of lnV_t and lnP_t would produce stationary residuals. This involves estimating the following regression:

$$lnV_t = \psi_0 + \psi_1 \ln P_t + e_t \tag{9}$$

The residuals from equation (9) are fitted into an auxiliary regression to estimate:

$$\Delta e_t = \gamma_1 e_{t-1} + \gamma_2 \Delta e_{t-1} + \xi_t. \tag{10}$$

Cointegration[27] is confirmed if the t-statistic for λ_1 is greater than 3.45.

Table 6 reports cointegration results for LACI and 52 broad indices and close competitors. These competitors are chosen based on publicly available data on YAHOO.com. Recall that both LACI and a particular asset must be non-stationary in the levels for a pairwise cointegration test. For the full sample period 2000-2023, LACI is cointegrated with three assets (Bond, US Treasury, and PCRPX). PCRPX (PIMCO Commodity Real Return Strategy) is a $5.25b size is rated three stars by Morningstar. Surprisingly, SPGSCI is not cointegrated with LACI, suggesting that LACI is truly a unique product. Overall, the results imply that LACI and most of its close substitute investment products do not share a common trend. Each may be responding to a different set of economic forces. Hence, using alternative assets would be very difficult to replicate LACI's performance. Moreover, in cases where we find cloning agents (cointegrated assets), they have a lower Sharpe ratio and may not provide the requisite diversification sought by portfolio managers.

In summary, LACI is genuinely a unique index. Combining commodity-specific stylized signals into a rules-based and disciplined commodity index allows the proposed strategy to offer superior returns compared to the competing brand name CTAs, hedge funds, mutual funds, and ETF/ETN products. In addition, LACI has the following characteristics: fully transparent, highly liquid, no leverage, fixed methodology (no style drift), and competitive Sharpe ratio.

[27] Note that the cointegration test outlined above has been criticized for its low power; however, the sample in this study covers a long period. For some of the more recent funds with a short history, the results may be questionable.

Robustness Test: Herding and LACI Performance

The final robustness test involves estimating LACI's sensitivity to herding. There is a vast amount of literature on herding. See McAleer and Randalj (2013) for a survey of the literature. Herding increases the exposure of an investment strategy to systemic risk when investors use the same factors to trade the same basket of stocks or commodities. As noted earlier, chasing similar factors to design investment strategies increases herding among investors and also the correlation between popular stocks, bonds, currencies, and commodities indices. Herding is analogous to mimicking others when making investment decisions, even when such correlated actions contradict the investors' private information or rationale (Banerjee (1992)). Correlated behavior is linked to investors using the same information and interpreting it similarly (Hirshleifer, Subrahmanyam, and Titman (1994)). Bikhchandani et al. (1992) claim that investors' sequential decision-making is responsible for herding. Their explanation suggests that cascading buying and selling decisions from following the leader (s) places more importance on the leaders' actions than private information.

Several authors have constructed empirical measures of herding to understand investor psychology and its effects on the market. For example, the LSV measure developed by Lakonishok, Shleifer, and Vishny (1992) uses observed percentages of buyers and sellers in a market to study herding among institutional traders. Christie and Huang (1995) define herding using the absolute cross-section deviation of returns (CSAD). A similar measure developed by Chang et al.(2000) looks at the squared dispersion of equity returns and the overall market return (CSSD). For example, these authors find ample evidence of herding in commodities, currencies, equities, and financial futures.

We estimate commodities-specific herding using the cross-sectional absolute standard deviations (CSAD) method. We assume that the SPGSCITR is the appropriate commodity benchmark in this paper. The CSAD measure is then calculated as follows:

$$CSADt = \frac{1}{N}\sum_{i=1}^{N} |ri,t - rm,t| \tag{11}$$

where $r_{i,t}$ are the daily returns from a particular commodity, and the $r_{m,t}$ is the daily return from the market index (SPGSCITR). We then calculated a weighted aggregate measure of herding for all commodities by their respective weights in LACI. The GARCH model for an asset is:

$$R_t = \delta_0 + \delta_1 CSAD_{COM,t} + \delta_2 CSAD_{FX,t} + \varepsilon_t \quad (12)$$

$$\varepsilon_t | \psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \quad (13)$$

$$\sigma_t^2 = \Omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j} \quad (14)$$

R_t in the mean equation (equation 12) is the daily returns from the asset under consideration. $CSAD_{COM,t}$ is the aggregate herding measure in the commodities market. Similarly, $CSAD_{FX,t}$ denotes herding in the currency market using the following bilateral major exchange rates (GBP, Euro, JPY, CAD, CHF, Skr) vis-à-vis the US dollar. The model is estimated assuming t-distribution for the error term. Similarly, we estimate several regressions for returns on all major asset classes and commodities strategies, including LACI. An increase in CSAD[28] indicates less herding. A positive sign for herding coefficient should be interpreted as a decrease in herding, leading to an increase in the asset's returns[29]. To avoid the contemporaneous relationship between LACI and herding, CSSD is lagged by one day.

The results are reported in Table 7. We find that in most cases and periods, the assets under study in this paper are not affected by herding in either the commodity or the currency market. In particular, the results suggest that LACI returns are insensitive to herding. The coefficients δ_1 and δ_2 are not significant. We consider this to be strong evidence of our investment strategy's effectiveness and reinforces our prior assumption that cascading investment decisions in the market lead to herding. The profitability of implementing a long-short-flat investment strategy as outlined in this paper remains robust. This also implies that herding is common in the commodities and currencies we considered, yet it fails to affect LACI and LACI-like investment strategies.

[28] We can also replace CSAD with CSSD, which is defined as:

$$CSSDt = \sqrt{\frac{\sum_{i=1}^{N}(ri,t - rm,t)^2}{N-1}}$$

We can also use commodities-specific herding using both the cross-sectional standard deviations (CSSD) and the results are similar where it is the aggregate weighted measure of herding for all the commodities considered in this study, with weights representing the proportion of each commodity in constructing LACI.

[29] Similarly, a negative sign for the coefficient of CSAD would indicate that a decrease in herding would lead to lower returns in LACI .

IV. Modifying the 60-40 Allocation with LACI

LACI's addition to a balanced portfolio (Balanced Portfolio) means changing the allocation guidelines and getting the desired outcomes in diversification, risk-adjusted performance, liquidity, and transparency. As a replacement for the 60-40 rule, the newly created Balanced Portfolio has the following components and features: SPY, Bloomberg Aggregate Bond Index, S&P DowJones Commodity Index (SPGSCI), and LACI. Using a constrained minimum variance portfolio optimization, we constructed two portfolios and compared their performance with a classic 60-40 allocation. The first portfolio is Blended+LACI portfolio and the weights are: SPY (40%), bond (4536%), and LACI (164%). We then replaced LACI with SPGSCI to create the second portfolio called Blended+SPGSCI and fixed the weights for the remaining assets. As noted earlier, the basic objective is to provide an alternative solution to the 60-40 rule, which has been increasingly scrutinized as the fixed income exposure is no longer expected to provide adequate protection in an equity downturn. Our Balanced portfolio (see Figure 8 and footnotes) provides diversified exposure to equities, fixed income, and commodities. Figure 8 shows the hypothetical value of $100 invested in each portfolio (including LACI as a separate asset) since 2000. As can be seen, the diversified portfolio with LACI added outperforms all other portfolios, including LACI itself. The diversified portfolio offers a more robust, investable "all-weather" alternative to other broadly diversified portfolio structures in the marketplace. The Balanced Portfolio's competitive return profile is achieved with a lower equity exposure than comparable products. This is due to the inclusion of LACI as a key diversifying portfolio component. LACI's effectiveness over meaningful time allows the Balanced Portfolio to maintain its exposures even during periods of equity market weakness. LACI's weighting and exposure methodology aligns with academic research, showing **commodity trend** investments provide superior diversification versus long-only and other alternative commodity exposures.

The Balanced Portfolio's performance has been attractive, notably surpassing many alternative investing strategies. During the period 2000-2023, the Balanced Portfolio has generated a 5.91% annualized return with a realized 5.31% annualized volatility. The Sharpe ratio is .65, with a maximum drawdown of -5.95%. Compared to that, the blended portfolio with SPGSCI generated annualized return and volatility of 5.28% and 6.68%, respectively. The Sharpe ratio was lower and max drawdown was larger. The traditional 60-40 equity/bond portfolio performance was 3.81% annual return with 6.77% volatility. The Sharpe ratio was the lowest.

Portfolio Diversification with LACI (Needs a new table with comparisons)

As noted earlier, interest in commodities soared partly because of their diversification benefits when included in traditional portfolios. However, changes in the commodity markets have created added complexity requiring more sophisticated alternative strategies in order to adapt. Over the past several years, there have been various so-called “liquid alternatives” trying to fill this void. Still, very few have provided a consistently viable alternative for a dedicated commodity strategy. Many commodity-related liquid alternatives are long-only strategies attempting to minimize the negative effects of rolling positions forward along the curve. Some of these strategies worked for a short period but were quickly arbitraged away. LACI is intended to provide a more palatable exposure to the commodity asset class by capturing large trends in commodities in both up and down commodity cycles. Thus, it offers meaningful diversification when it is most needed. The table below shows the correlations among SPGSCITR, LACI, and the S&P 500 over different periods.

[redacted]

Correlation Period	SPGSCITR - SPY	LACITR - SPY	LACITR-SocGen CTA Index	LACI - LBUSTRUU	SPY - VWELX	SPY - Balanced Portfolio
2000 to 2004	(0.03)	(0.07)	0.12	(0.08)	0.83	0.96
2005 to 2009	0.41	(0.30)	0.44	(0.13)	0.96	0.94
2010 to 2014	0.66	(0.08)	0.44	(0.17)	0.98	0.95
2015 to 2019	0.46	(0.10)	0.30	0.09	0.97	0.93
2020 to 6/2023	0.43	(0.31)	0.34	(0.20)	0.98	0.96

SPY is the SPDR S&P 500 ETF Trust

LACITR is the Liquid Alternative Commodity Index - Total Return

SPGSCITR is the S&P Goldman Sachs Commodity Index - Total Return

SocGen CTA Index is the Societe General CTA Index

LBUSTRUU is the Bloomberg US Aggregate Bond Index

VWELX is the Vanguard Wellington Fund

Balanced Portfolio is comprised of 51% SPY, 34% VBMFX, and 15% LACITR

[redacted]

LACI has consistently kept its diversifying characteristics, while the SPGSCITR has become a less effective diversifier. Overall, Sharpe ratios and drawdowns improve significantly by replacing the passive long-only commodity exposure with a more active commodity allocation. Table 8 presents salient statistics of adding LACI to construct a series of simplified all-weather type portfolios, starting in 1993. The value-added monthly index (VAMI) for the selected portfolios are shown in Figure 9. The results indicate that the addition of LACI improves the risk-return performance of the portfolios. We believe LACI truly becomes the all-weather diversifier that is prudent for any investor utilizing the commodity markets. By focusing on some simple Equity/Bond portfolio-weighted exposures and adding a 20% exposure to LACI, we can then see how this mix compares to the actual performance of other widely held investments. As mentioned previously but worth noting again, all returns presented throughout this paper for the LACI include interest earned on a fully collateralized basis and are net of expected transaction costs and implied. 85% annualized management fee. This normalizes the returns in a manner that makes comparisons to other investable products more representative.

V. Conclusions

The 60-40 equity/bond allocation rule has become suspect due to the extended period of low interest rates. With massive quantitative easing with trillions of dollars worldwide, the 60-40 strategy needs serious modification. As interest rates have fallen worldwide, fixed income products have not generated the kind of income and diversification they once delivered. Investors worldwide are now dealing with a new paradigm where historically negatively correlated assets have reversed and are now positively correlated. Many investors searching for negatively correlated diversifying assets have turned to commodities. However, simply adding passive long-only commodity exposure to a 60-40 portfolio has fared poorly due to the failure to consider contango/backwardation oscillation. Also, the realization that falling commodity prices can be just as detrimental to equity and bond markets as rapidly rising prices require a more active exposure to this asset class. The rising correlation between the commodity asset class and equities diminishes the utility of plain passive long-only commodity exposure.

Additionally, the structural changes in the commodity futures forward markets indicate that the cost of maintaining passive long-only exposures may continue to diminish the overall effectiveness of this style of allocation. Typically, popular commodity-based ETFs, ETN's, and listed managed futures strategies are expected to offer stable investment returns with acceptable levels of volatility. In reality, they have not addressed significant paradigm shifts in the commodity markets, including backwardation-contango oscillation, time-varying correlations, factor crowding, a massive flow of funds populating long-only strategies, and significant transaction costs associated with the requisite periodic rolls. What is equally puzzling is that investors continue to pour money into these strategies despite the underperformance associated with an overwhelming number of these commodity-related alternative products.

This paper demonstrates how the Liquid Alternative Commodity Index (LACI)[30] can be used to modify the traditional 60-40 equity-fixed income allocation scheme. The index allows an investor with a passive long-only commodity allocation to seek a more active exposure to deal with broad economic and political changes affecting commodities markets. The proposed long/short investment strategy uses proprietary algorithms to generate commodity positions. It is a transparent, liquid strategy and provides more stable returns than the widely recognized long-only commodity index benchmarks. The proposed investment can handle systemic exposure of the selected commodity contracts to the economy and the equity market and extract high-quality signals when commodity futures contracts oscillate between contango and backwardation. The low-cost and high Sharpe ratio makes LACI beat many comparable programs. Finally, a balanced portfolio created by adding LACI to a portfolio of fixed income and equity assets to diversify portfolio risk and generates higher risk-adjusted returns than most brand-name commodity-focused CTAs, hedge funds, alternative mutual funds, and ETFs.

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[30] Returns from this alternative index shown throughout this paper are NET of expected transaction costs and a 85% implied annualized management fee.

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Figure 1

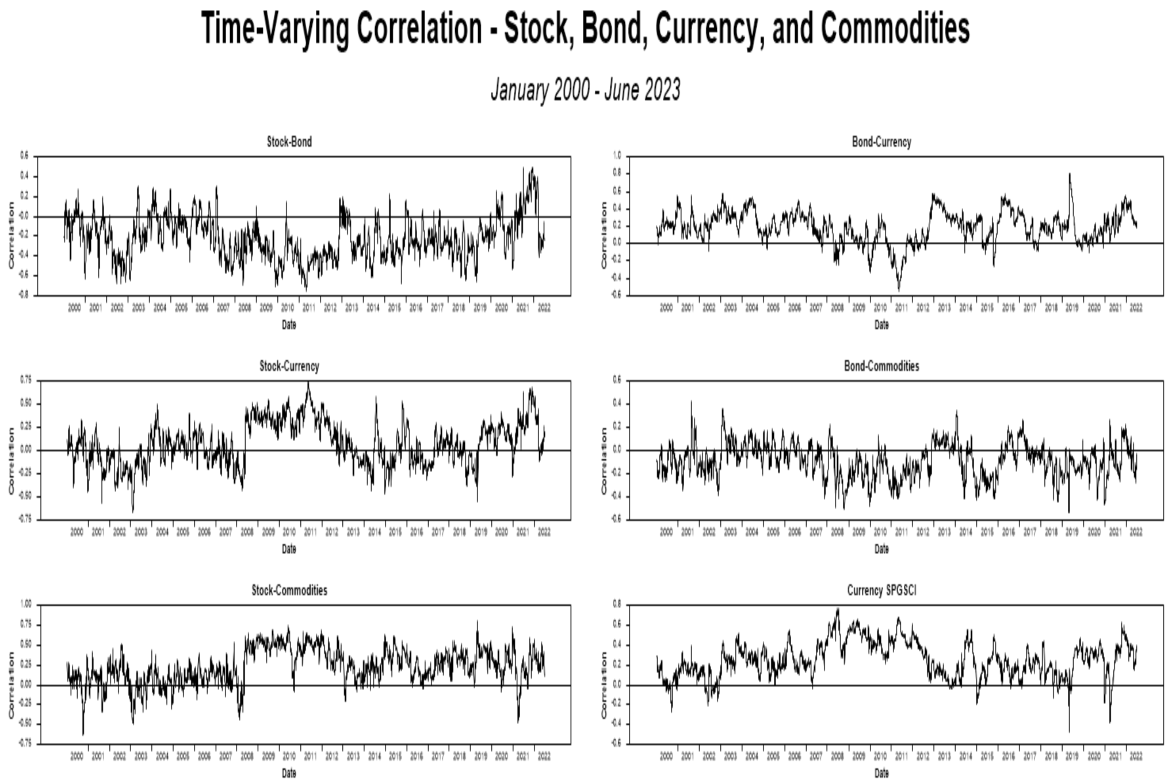


Figure 2

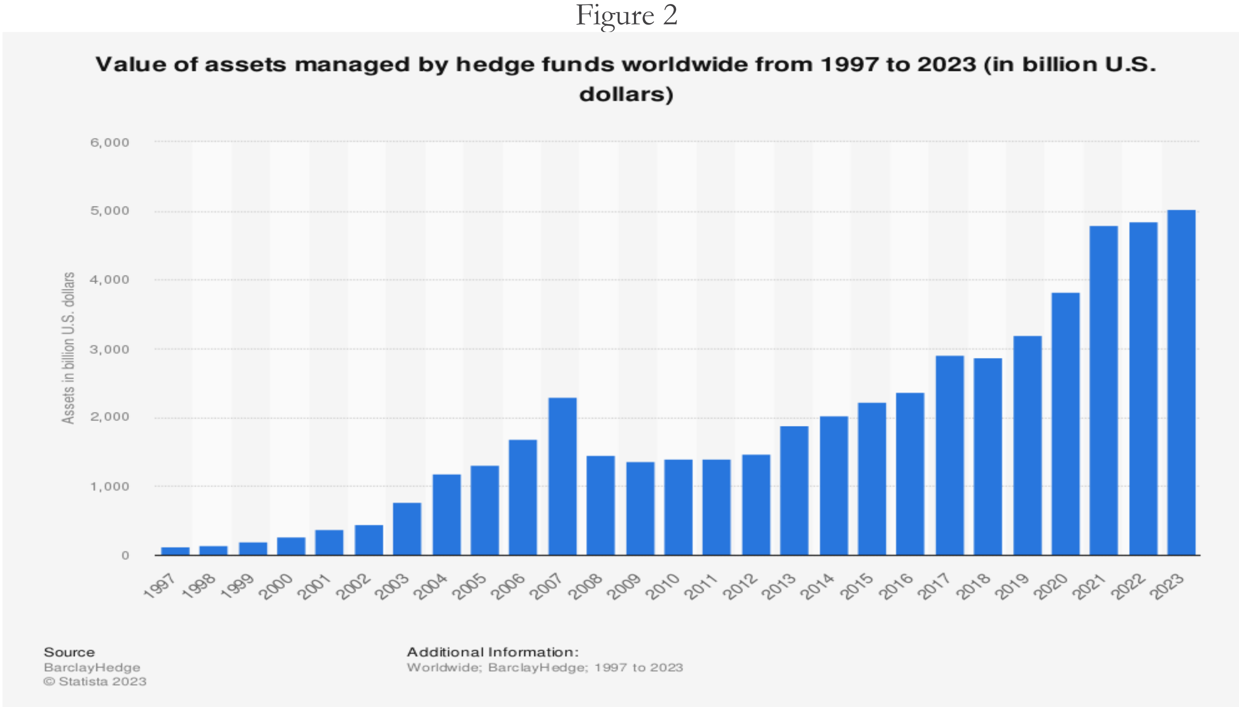
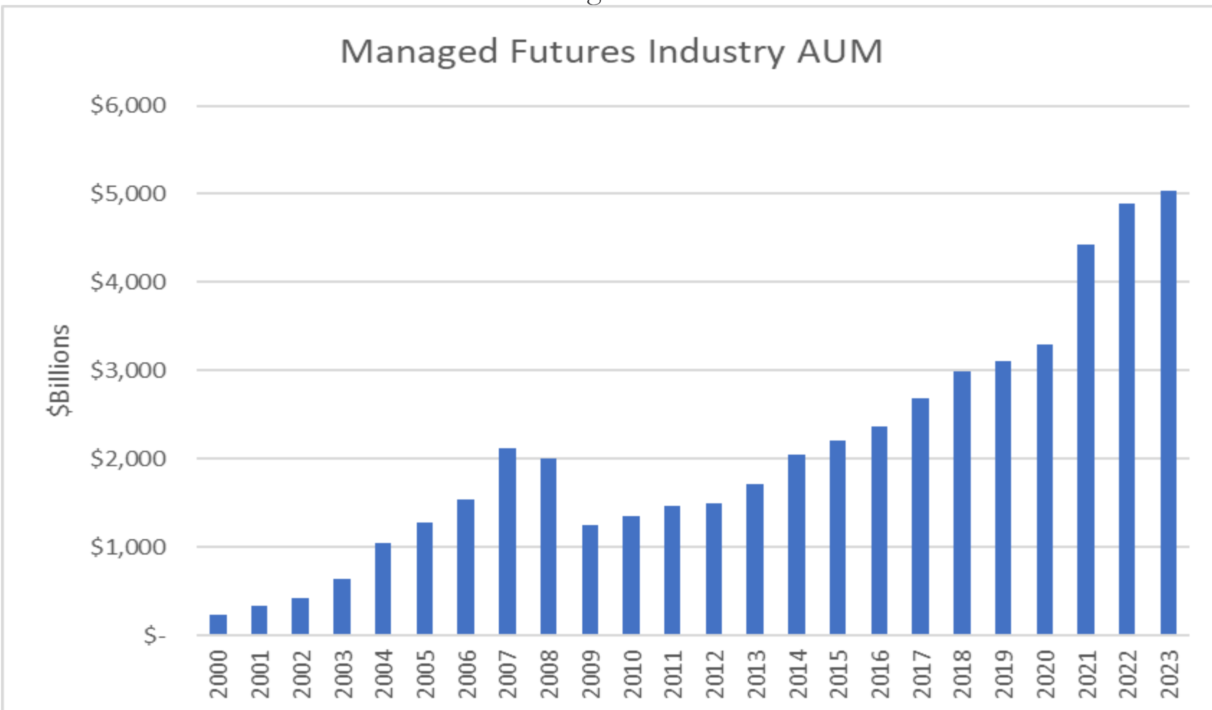


Figure 3



Source: www.barclayhedge.com

Figure 4

Futures Curve Showing Backwardation in WTI Crude Oil
(10/1/1997)

Figure 5
Futures Curve Showing Contango in WTI Crude Oil
(11/30/2015)

Figure 6

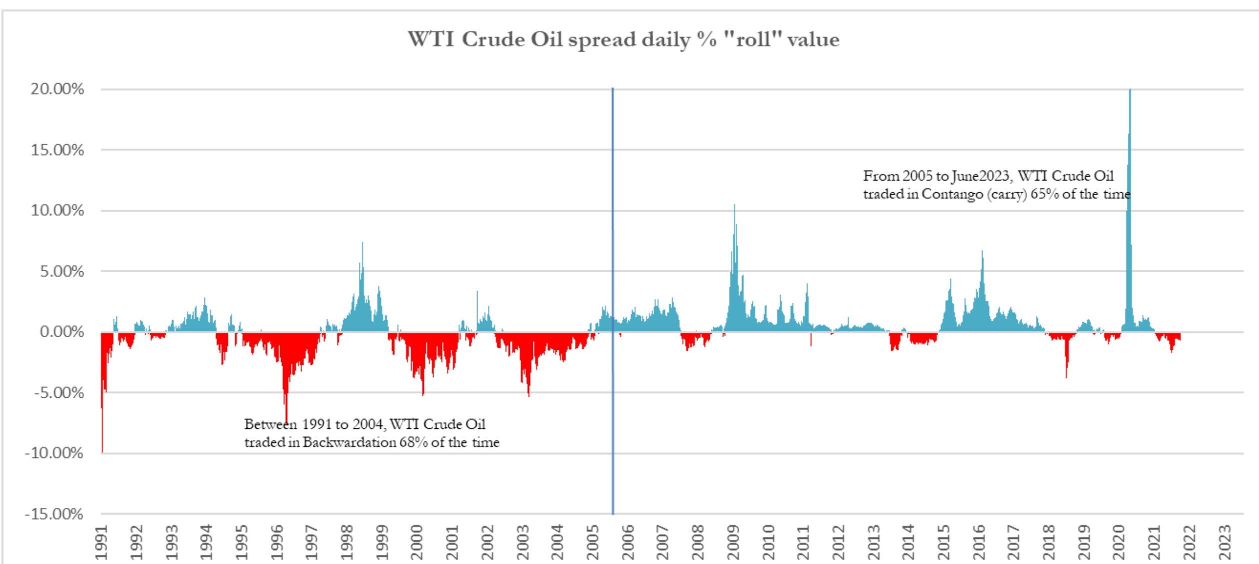


Figure 7

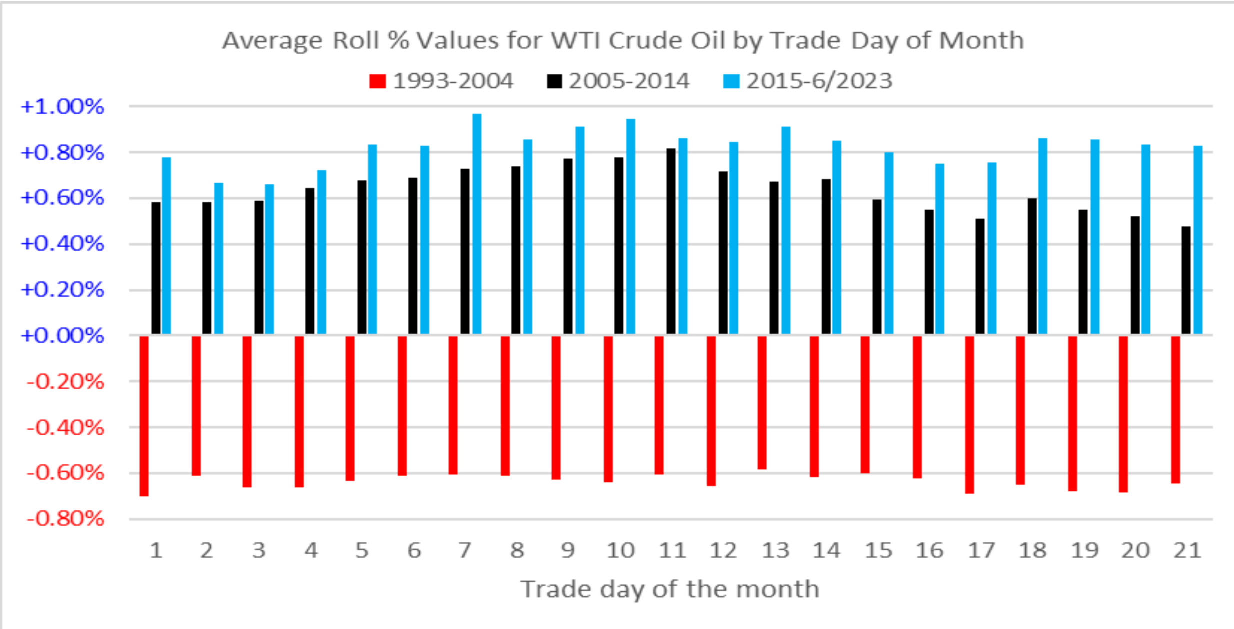

Average Roll % Values for WTI Crude Oil by Trade Day of Month
1993-2004
2005-2014
2015-6/2023
+1.00%
+0.80%
+0.60%
+0.40%
+0.20%
+0.00%
-0.20%
-0.40%
-0.60%
-0.80%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21
Trade day of the month

TABLE 1

Panel A: Attribution analysis by Period

Period	LACITR Ann Ret%	LACITR StDev	Max Weighted Contribution to Index Return	Commodity	Max Contribution to Index Volatility	Commodity	Min Weighted Contribution to Index Return	Commodity	Min Contribution to Index Volatility	Commodity
2000 to 2004	+ 6.93%	12.48%	+ 6.85%	Natural Gas	6.17%	Crude Oil	- 4.55%	Gold	0.12%	Feeder Cattle
2005 to 2009	+ 24.42%	18.33%	+ 35.04%	Crude Oil	8.02%	Crude Oil	- 2.49%	Wheat	0.12%	Feeder Cattle
2010 to 2014	+ 6.65%	13.61%	+ 14.18%	Crude Oil	5.86%	Crude Oil	- 2.73%	Soybeans	0.10%	Feeder Cattle
2015 to 2019	+ 0.34%	13.00%	+ 5.57%	Natural Gas	5.39%	Crude Oil	- 6.25%	HG Copper	0.15%	Cocoa
2020 to June-2023	+ 8.44%	18.90%	+ 8.10%	HG Copper	8.30%	Crude Oil	- 2.50%	Wheat	0.06%	Platinum

Panel B: Aggregate Position Summary by Period

	--- AVERAGE ---		------------ SELECTED POSITIONS ------------				------------ SELECTED POSITIONS ------------			
Period	% Long	% Short	Max Long	Commodity	Max Short	Commodity	Min Long	Commodity	Min Short	Commodity
2000 to 2004	52.36%	47.64%	76.67%	Platinum	73.33%	Coffee	26.67%	Coffee	23.33%	Platinum
2005 to 2009	52.29%	47.71%	76.67%	Platinum	71.67%	Lean Hogs	28.33%	Lean Hogs	23.33%	Platinum
2010 to 2014	48.75%	51.25%	66.67%	FD Cattle	70.00%	Wheat	30.00%	Wheat	33.33%	FD Cattle
2015 to 2019	42.15%	57.85%	56.67%	Gas Oil	78.33%	Coffee	21.67%	Coffee	43.33%	Gas Oil
2020 to June-2023	40.21%	59.79%	48.33%	Sugar #11	41.67%	Natural Gas	26.67%	Natural Gas	20.00%	RBOB

Panel C: LACI vs comparable listed products

Program	Symbol	Program Start Date	Fees	YTD	3 yr[1]	5 yr[1]	10 yr[1]	Since Inception	Sharpe	Max DD
Liquid Alternative Commodity Index-TR	**LACITR[2]**	**12/1999 (23.50 years)**	**n/a**	**+7.92%**	**+6.63%**	**+4.00%**	**+5.43%**	**+9.11%**	**0.49**	**-22.79%**
SPDR Gold Shares	GLD	11/2004 (18.58 years)	+0.40%	+5.09%	0.02	+8.48%	+4.11%	+7.68%	0.37	-42.91%
iShares Silver Trust	SLV	04/2006 (17.17 years)	+0.50%	-5.13%	0.07	+6.64%	+0.97%	+2.44%	0.04	-72.16%
Invesco Optimum Yield Diversified Commodity Strategy	PDBC	11/2014 (8.58 years)	+0.59%	-7.95%	0.22	+5.66%	n/a	+1.61%	0.02	-44.52%
Invesco DB Commodity Index Tracking Fund	DBC	02/2006 (17.33 years)	+0.85%	-7.91%	0.23	+5.86%	-0.67%	+0.42%	(0.04)	-74.55%
PIMCO CommoditiesPLUS Strategy Fund Class I-2	PCLPX	06/2010 (13.00 years)	+0.84%	-4.13%	0.28	+8.13%	+1.89%	+3.07%	0.11	-63.62%
iShares S&P GSCI Commodity-Indexed Trust	GSG	07/2006 (16.91 years)	+0.75%	-8.20%	0.23	+1.71%	-4.47%	-5.50%	(0.28)	-88.68%
iPath Bloomberg Commodity Index Total Return	DJP	10/2006 (16.66 years)	+0.70%	-9.31%	0.20	+4.65%	-1.75%	-2.73%	(0.21)	-77.30%
iShares Commodities Select Strategy ETF	COMT	10/2014 (8.66 years)	+0.48%	-7.84%	0.19	+3.22%	n/a	-0.27%	(0.08)	-46.59%
PIMCO CommodityRealReturn Strategy Fund Class I-2	PCRPX	04/2008 (15.16 years)	+0.92%	+0.94%	0.23	+7.34%	+0.62%	+7.50%	0.09	-59.95%
Columbia Commodity Strategy Fund Advisor Class	CCOMX	03/2013 (10.25 years)	+0.86%	-7.88%	0.19	+5.32%	-1.09%	-2.12%	(0.22)	-55.04%
Credit Suisse Commodity Return Strategy Fund Class A	CRSAX	12/2004 (18.49 years)	+1.05%	-8.86%	0.18	+4.90%	-1.03%	-1.09%	(0.15)	-72.18%
Invesco Balanced-Risk Commodity Strategy Fund Class A	BRCAX	11/2010 (12.58 years)	+1.40%	-5.33%	0.16	+4.03%	+0.07%	-1.10%	(0.13)	-58.24%
MFS Commodity Strategy Fund Class A	MCSAX	06/2010 (13.00 years)	+1.13%	-8.47%	0.17	+4.27%	-0.97%	-0.70%	(0.10)	-63.54%
ALPS/CoreCommodity Management CompleteCommodities Strategy Fund Class A	JCCSX	06/2018 (5.00 years)	+1.45%	-8.65%	0.20	+4.59%	n/a	+4.59%	0.15	-35.97%
VanEck CM Commodity Index Fund Class A	CMCAX	12/2010 (12.50 years)	+0.95%	-5.65%	0.21	+6.82%	+0.53%	-0.96%	(0.12)	-59.26%
Credit Suisse Trust Commodity Return Strategy Portfolio	CCRSX	03/2006 (17.25 years)	+1.05%	-8.57%	0.18	+4.77%	-1.04%	-1.49%	(0.16)	-71.80%
DoubleLine Strategic Commodity Fund Class I	DBCMX	05/2015 (8.08 years)	+1.11%	-4.79%	0.21	+3.90%	n/a	+3.57%	0.15	-35.22%
WisdomTree Continuous Commodity Index Fund	GCC	01/2008 (15.41 years)	+0.55%	-6.37%	0.14	+4.12%	-1.12%	-2.05%	(0.18)	-60.82%
Goldman Sachs Commodity Strategy Fund Class A	GSCAX	04/2007 (16.17 years)	+0.93%	-12.15%	0.17	-1.25%	+8.86%	+3.36%	0.03	-75.42%
AQR Risk-Balanced Commodities Strategy Fund Class I	ARCIX	07/2012 (10.91 years)	+1.27%	-1.79%	0.31	+12.77%	+4.29%	+1.96%	0.06	-51.80%
First Trust Global Tactical Commodity Strategy Fund	FTGC	10/2013 (9.66 years)	+0.95%	-5.60%	0.21	+6.11%	n/a	-0.51%	(0.12)	-57.64%

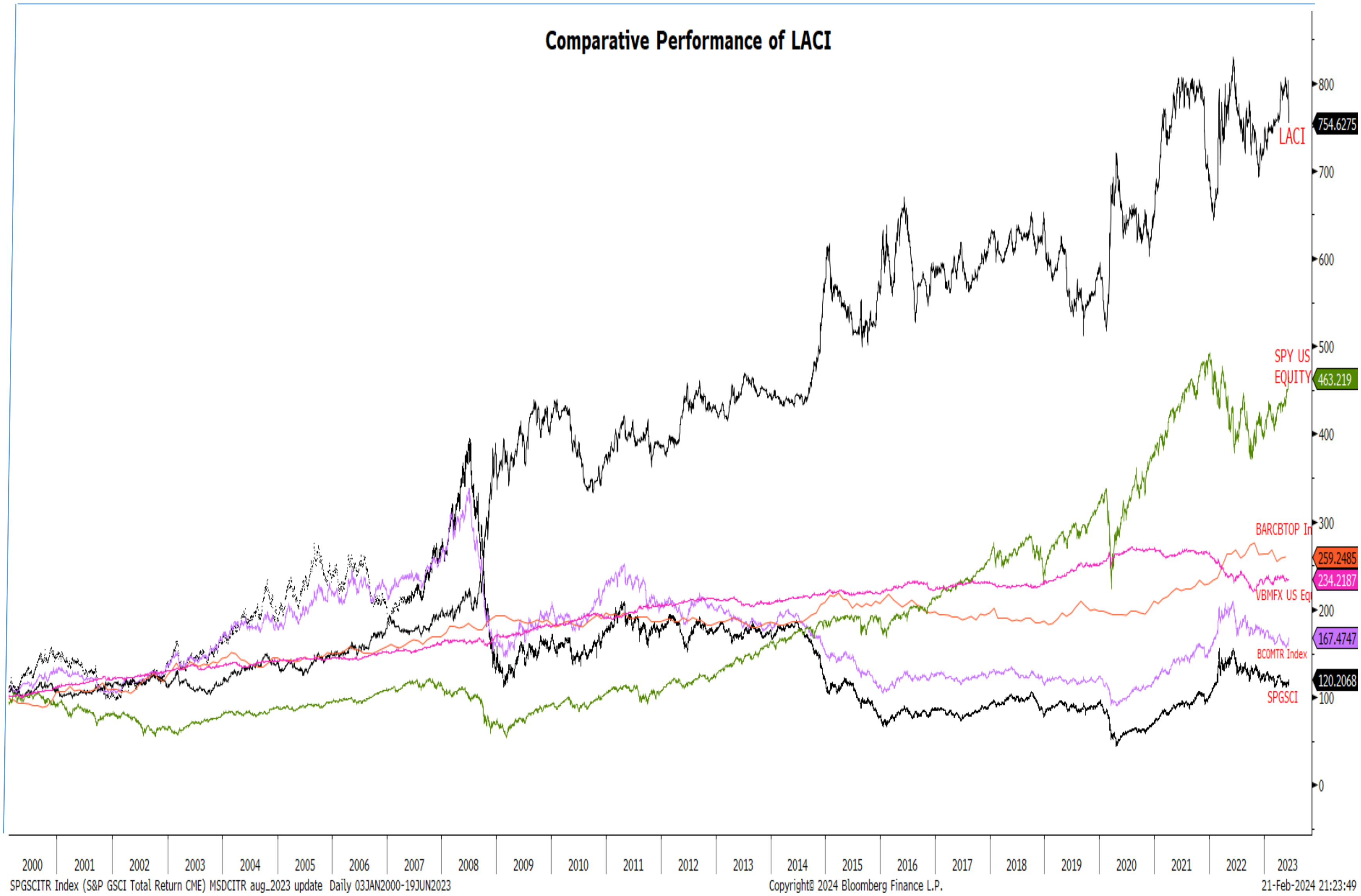
Data shown is through 6/30/2023

1 Annualized

2 LACITR returns are HYPOTHETICAL and do not account for any fees

NOTE: The Elements Linked ro Rogers International Commodity Fund (RJI) and the Neuberger Berman Commodity Strategy Fund Class A (NRBAX), included in the previous version of this paper, have since closed

Figure 8


Comparative Performance of LACI
800
754.6275
LACI
700
600
500
SPY US
EQUITY
463.219
400
300
BARCBTOP In
259.2485
234.2187
VBMFX US Eq
200
167.4747
BCOMTR Index
120.2068
SPGSCI
100
0
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
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2017
2018
2019
2020
2021
2022
2023
SPGSCITR Index (S&P GSCI Total Return CME) MSDCITR aug_2023 update Daily 03JAN2000-19JUN2023
Copyright© 2024 Bloomberg Finance L.P.
21-Feb-2024 21:23:49

Table 2

Historical Performance of Equities, Managed Futures, a Long Only Commodity Index and LACI© during Crises

Period	Description of Crisis	Equity Returns [1]	Managed Futures Returns [2]	SPGSCITR Returns [3]	LACITR Returns [4]
SEP 2000 - NOV 2000	USS Cole; Mad Cow outbreak; Bush v Gore	- 5.93%	- 1.55%	- 1.15%	- 0.46%
FEB 01 - MAR 01	Bush inaugurated; US and Britain attack Iraq	- 14.61%	+ 5.48%	- 5.26%	+ 4.08%
JUL 01 - SEP 01	Events leading up to 9/11 attacks	- 14.49%	+ 2.71%	- 9.89%	+ 0.90%
APR 02 - SEP 02	Enron and WorldCom; End of tech bubble	- 28.01%	+ 17.16%	+ 11.55%	+ 6.09%
DEC 02 - FEB 03	War in Iraq; SARS outbreak	- 9.22%	+ 14.90%	+ 32.63%	+ 7.24%
JUN 08 - FEB 09	Global financial crisis (The Great Recession)	- 46.32%	+ 7.18%	- 64.66%	+ 74.95%
MAY 10 - JUN 10	Greek crisis	- 12.71%	- 1.65%	- 12.83%	- 9.81%
MAY 11 - SEP 11	Eurozone debt crisis; US credit downgrade	- 16.22%	- 3.66%	- 22.14%	- 2.99%
APR 12 - MAY 12	Continuing European crises	- 6.63%	+ 3.12%	- 13.42%	+ 12.43%
AUG 15 - SEP 15	Chinese currency crisis	- 8.49%	- 0.74%	- 6.05%	+ 1.99%
DEC 15 - JAN 16	Draghi stimulus fiasco; first Fed hike since 2006	- 6.62%	+ 2.77%	- 13.35%	+ 11.37%
FEB 20 - APR 20	Corona Virus pandemic	- 9.18%	- 1.14%	- 41.60%	+ 27.37%
JAN 22 - SEP 22	Fed rate hikes, Ukraine war, inflation fears	- 23.93%	- 100.00%	+ 21.80%	+ 10.42%
		- 202.36%	- 55.43%	- 124.37%	+ 143.59%

1 Equity Returns represented by the S&P 500 Total Return Index

2 Managed Futures Returns represented by the Societe General CTA Index

3 SPGSCI-TR is the S&P Goldman Sachs Commodity Index - Total Return - a collateralized long only, production weighted commodity index

4 LACI returns shown are ***HYPOTHETICAL*** *net of expected transaction costs and a 1.00% annualized management fee*

Table 3
Correlation Matrix
Panel A: 2000 - 2023

Variables	SPY	Bond	Muni	US Treasury	High Yield	MBS	REITS	Currency	Commodities
SPY									
Bond	-0.207								
Muni	-0.063	0.443							
US Treasury	-0.304	0.884	0.441						
High Yield	0.348	0.112	0.225	-0.049					
MBS	-0.087	0.825	0.406	0.795	0.128				
REITS	0.689	-0.083	-0.011	-0.155	0.229	-0.003			
Currency	0.110	0.191	0.124	0.163	0.173	0.219	0.120		
Commodities	0.278	-0.097	-0.040	-0.168	0.260	-0.050	0.184	0.283	
LACI	-0.151	0.035	0.022	0.075	-0.112	0.010	-0.112	-0.013	-0.078

Correlation Matrix
Panel B: 2000 - 2004

Variables	SPY	Bond	Muni	US Treasury	High Yield	MBS	REITS	Currency	Commodities
SPY									
Bond	-0.202								
Muni	-0.118	0.549							
US Treasury	-0.276	0.872	0.626						
High Yield	-0.001	0.089	0.086	0.060					
MBS	-0.179	0.834	0.556	0.870	0.085				
REITS	0.455	-0.058	-0.018	-0.104	0.041	-0.049			
Currency	-0.153	0.304	0.260	0.328	0.075	0.320	-0.032		
Commodities	-0.013	-0.007	0.030	-0.007	0.014	-0.005	-0.075	0.124	
LACI	-0.079	0.043	0.037	0.047	0.036	0.038	-0.139	0.053	0.332

Correlation Matrix
Panel C: 2005 - 2009

Variables	SPY	Bond	Muni	US Treasury	High Yield	MBS	REITS	Currency	Commodities
SPY									
Bond	-0.233								
Muni	-0.198	0.404							
US Treasury	-0.344	0.842	0.405						
High Yield	0.329	0.087	0.192	-0.110					
MBS	-0.144	0.822	0.382	0.756	0.081				
REITS	0.774	-0.180	-0.192	-0.261	0.096	-0.115			
Currency	0.186	0.132	0.005	0.094	0.196	0.125	0.100		
Commodities	0.308	-0.109	-0.066	-0.227	0.264	-0.077	0.169	0.421	
LACI	-0.187	0.057	0.009	0.128	-0.148	0.012	-0.094	-0.037	-0.192

Correlation Matrix
Panel D: 2010 - 2014

Variables	SPY	Bond	Muni	US Treasury	High Yield	MBS	REITS	Currency	Commodities
SPY									
Bond	-0.460								
Muni	-0.223	0.472				.	.		
US Treasury	-0.507	0.882	0.512			.	.	.	
High Yield	0.397	-0.036	-0.017	-0.183		.	.	.	
MBS	-0.245	0.790	0.466	0.779	0.036		.	.	
REITS	0.822	-0.272	-0.050	-0.301	0.322	-0.060		.	.
Currency	0.396	-0.038	-0.035	-0.108	0.203	0.107	0.366		.
Commodities	0.494	-0.231	-0.127	-0.311	0.348	-0.125	0.399	0.445	
LACI	-0.127	0.042	0.039	0.080	-0.075	0.014	-0.109	-0.101	-0.133

Correlation Matrix
Panel D: 2015 - 2019

Variables	SPY	Bond	Muni	US Treasury	High Yield	MBS	REITS	Currency	Commodities
SPY									
Bond	-0.308								
Muni	-0.213	0.599							
US Treasury	-0.361	0.900	0.680						
High Yield	0.470	-0.110	-0.123	-0.222					
MBS	-0.238	0.838	0.627	0.875	-0.085				
REITS	0.570	0.138	0.127	0.104	0.282	0.152			
Currency	-0.058	0.187	0.107	0.192	-0.031	0.210	0.008		
Commoditie	0.329	-0.167	-0.149	-0.226	0.383	-0.137	0.117	0.182	
LACI	-0.122	0.070	0.028	0.072	-0.134	0.053	-0.099	0.009	-0.305

Correlation Matrix
Panel D: 2020 - 2023

Variables	SPY	Bond	Muni	US Treasury	High Yield	MBS	REITS	Currency	Commodities
SPY									
Bond	0.003								
Muni	0.253	0.354							
US Treasury	-0.143	0.926	0.240						
High Yield	0.591	0.309	0.523	0.061					
MBS	0.134	0.862	0.289	0.799	0.278				
REITS	0.828	0.065	0.303	-0.076	0.586	0.164			
Currency	0.222	0.340	0.288	0.264	0.380	0.363	0.196		
Commoditie	0.346	-0.042	0.026	-0.129	0.328	0.014	0.290	0.196	
LACI	-0.206	-0.023	0.020	0.037	-0.184	-0.032	-0.196	0.004	-0.034

Table 4: Exposure to Aggregate Markets (2000-2023)

Asset	Intercept	SPY	Bond	DXY	SPGSCI	ARCH0	ARCH1	GARCH1	TDFI
ABYIX	0.035	0.025	-0.141	-0.385	-0.003	0.081	0.175	0.515	0.196
	(3.89)***	(3.02)***	(-4.47)***	(-18.53)***	(-0.36)	(4.63)***	(4.99)***	(6.20)***	(11.25)***
AHLIX	0.036	-0.012	-0.104	-0.258	-0.005	0.132	0.177	0.471	0.234
	(3.46)***	(-1.18)	(-2.82)***	(-10.92)***	(-0.55)	(4.95)***	(4.48)***	(5.34)***	(13.08)***
AMFNX	0.07	0.027	-0.524	-0.286	0.055	0.279	0.174	0.39	0.215
	(4.14)***	(1.91)*	(-9.42)***	(-6.87)***	(3.95)***	(4.72)***	(4.14)***	(3.64)***	(11.82)***
AQMRX	0.038	-0.039	-0.344	-0.203	-0.046	0.058	0.091	0.758	0.197
	(3.35)***	(-3.66)***	(-8.69)***	(-7.87)***	(-4.74)***	(3.27)***	(3.96)***	(12.57)***	(10.28)***
ASFYX	0.036	0.159	0.154	-0.228	0.025	0.073	0.141	0.742	0.206
	(3.26)***	(13.10)***	(3.55)***	(-8.95)***	(2.29)**	(5.55)***	(6.60)***	(22.30)***	(16.10)***
BCD	-0.005	0.043	0.003	0.212	0.598	0.004	0.077	0.914	0.224
	(-0.50)	(4.57)***	(0.11)	(8.14)***	(65.61)***	(2.57)**	(5.22)***	(62.06)***	(8.23)***
BCI	-0.011	0.058	0.043	0.189	0.705	0.004	0.1	0.887	0.198
	(-1.32)	(6.21)***	(1.40)	(7.89)***	(78.25)***	(3.32)***	(5.99)***	(54.45)***	(8.49)***
BCSAX	-0.023	0.334	0.002	0.348	0.561	0.003	0.063	0.921	0.119
	(-3.75)***	(50.96)***	(0.09)	(22.91)***	(86.13)***	(3.50)***	(6.92)***	(84.83)***	(7.87)***
BCSKX	-0.015	0.283	-0.056	0.426	0.567	0.004	0.087	0.897	0.142
	(-1.60)	(33.54)***	(-1.71)*	(16.35)***	(62.47)***	(2.36)**	(4.93)***	(45.77)***	(5.33)***
BRCAX	-0.004	-0.002	0.096	0.222	0.654	0.003	0.068	0.92	0.104
	(-0.53)	(-0.28)	(3.87)***	(13.86)***	(103.50)***	(3.38)***	(7.44)***	(87.08)***	(6.51)***
CCOMX	-0.005	-0.005	0.061	0.119	0.739	0.003	0.075	0.903	0.135
	(-0.92)	(-0.77)	(2.75)***	(8.60)***	(130.20)***	(3.97)***	(6.57)***	(65.34)***	(9.77)***
CCRSX	-0.003	-0.001	0.059	0.119	0.767	0.003	0.063	0.912	0.142
	(-0.69)	(-0.15)	(3.34)***	(11.31)***	(181.08)***	(4.77)***	(7.79)***	(84.88)***	(15.90)***
CCSRX	-0.006	-0.006	0.07	0.111	0.75	0.003	0.078	0.896	0.139
	(-1.19)	(-0.99)	(3.20)***	(8.37)***	(136.77)***	(4.13)***	(6.73)***	(61.06)***	(9.93)***
CMCAX	0	0.033	-0.06	0.087	0.744	0.005	0.069	0.873	0.084
	(-0.05)	(6.57)***	(-3.26)***	(7.43)***	(157.14)***	(4.02)***	(6.26)***	(40.74)***	(6.31)***
CMDY	-0.012	0.044	-0.002	0.241	0.605	0.004	0.108	0.884	0.151
	(-1.13)	(4.54)***	(-0.06)	(8.60)***	(64.18)***	(2.30)**	(5.61)***	(48.11)***	(5.45)***
COM	0.02	-0.013	0.05	0.147	0.252	0.012	0.084	0.868	0.172
	(1.88)*	(-1.41)	(1.47)	(5.53)***	(27.21)***	(3.37)***	(5.12)***	(36.35)***	(7.06)***
COMT	-0.005	0.179	-0.196	0.042	0.843	0.008	0.136	0.834	0
	(-0.58)	(27.79)***	(-7.26)***	(2.24)**	(137.64)***	(7.43)***	(11.78)***	(63.41)***	(999.00)***
CRSAX	-0.007	-0.002	0.066	0.113	0.775	0.003	0.069	0.905	0.128
	(-1.51)	(-0.47)	(3.80)***	(11.34)***	(190.56)***	(4.86)***	(7.99)***	(79.19)***	(12.59)***
DBC	-0.001	0.072	0.012	0.033	0.896	0.003	0.108	0.88	0.158
	(-0.29)	(13.95)***	(0.59)	(2.93)***	(182.97)***	(4.86)***	(9.86)***	(82.81)***	(10.99)***
DBMF	0.061	0.043	-0.585	-0.289	0.073	0.132	0.193	0.626	0.208
	(2.95)***	(2.48)**	(-9.62)***	(-5.72)***	(4.84)***	(3.21)***	(3.68)***	(7.22)***	(7.82)***
DJP	-0.012	0.065	0.078	0.145	0.799	0.005	0.075	0.904	0.125
	(-2.01)**	(11.12)***	(3.45)***	(10.73)***	(144.77)***	(4.50)***	(8.32)***	(80.23)***	(9.77)***
EVOIX	0.036	0.118	0.251	-0.317	-0.038	0.028	0.101	0.832	0.165
	(3.56)***	(11.26)***	(6.47)***	(-12.93)***	(-3.84)***	(4.32)***	(6.29)***	(32.15)***	(9.82)***
FCSSX	-0.008	0.031	0.087	0.133	0.718	0.012	0.11	0.808	0.184
	(-1.52)	(5.12)***	(4.03)***	(10.37)***	(131.04)***	(5.83)***	(6.84)***	(34.87)***	(17.70)***
FIFGX	-0.008	0.04	0.328	0.232	0.725	0.004	0.104	0.885	0.184
	(-0.76)	(4.15)***	(9.91)***	(8.29)***	(76.35)***	(2.35)**	(4.63)***	(39.76)***	(6.27)***
GAAVX	0.016	0.066	-0.186	0.151	0.018	0.01	0.154	0.756	0.228
	(2.13)**	(9.50)***	(-8.28)***	(7.64)***	(2.93)***	(3.44)***	(4.27)***	(16.49)***	(8.15)***
GCC	-0.025	0.077	0.003	0.22	0.783	0.034	0.078	0.752	0.126
	(-1.54)	(5.13)***	(0.07)	(5.79)***	(56.95)***	(2.07)**	(2.56)**	(7.88)***	(4.74)***

Asset	Intercept	SPY	Bond	DXY	SPGSCI	ARCH0	ARCH1	GARCH1	TDFI
GFIRX	0.02 (2.66)***	0.104 (11.92)***	-0.115 (-3.65)***	-0.158 (-8.37)***	-0.018 (-2.40)**	0.021 (5.30)***	0.155 (6.73)***	0.778 (29.42)***	0.214 (13.66)***
GLD	0.021 (2.08)**	-0.048 (-4.64)***	0.753 (20.03)***	0.766 (32.71)***	0.203 (21.40)***	0.008 (4.08)***	0.062 (8.49)***	0.931 (124.48)***	0.195 (13.63)***
GSG	-0.005 (-0.93)	0.069 (11.55)***	-0.034 (-1.61)	-0.101 (-7.51)***	1.093 (221.79)***	0.005 (7.98)***	0.11 (16.66)***	0.873 (120.55)***	0 (999.00)***
JCCSX	-0.02 (-2.21)**	0.19 (24.74)***	-0.102 (-3.56)***	0.285 (11.31)***	0.703 (86.58)***	0.003 (2.33)**	0.078 (4.76)***	0.905 (47.10)***	0.116 (5.03)***
LACI	0.003 (0.40)	-0.042 (-5.58)***	-0.005 (-0.16)	-0.063 (-3.55)***	0.536 (70.95)***	0.019 (6.73)***	0.213 (13.18)***	0.795 (66.35)***	0.188 (13.82)***
LCSIX	0.011 (1.56)	-0.016 (-2.17)**	0.148 (6.05)***	0.014 (0.79)	0.023 (3.30)***	0.006 (4.05)***	0.113 (7.41)***	0.866 (54.06)***	0.188 (9.25)***
LFMIX	0.03 (3.53)***	0.059 (7.05)***	0.212 (6.66)***	-0.243 (-12.42)***	0.024 (3.12)***	0.078 (5.25)***	0.175 (5.77)***	0.6 (10.15)***	0.223 (13.51)***
LOTIX	0.056 (3.65)***	0.107 (7.64)***	-0.084 (-1.60)	-0.314 (-9.16)***	0.017 (1.35)	0.265 (4.28)***	0.151 (4.34)***	0.466 (4.44)***	0.187 (11.03)***
MCSAX	-0.001 (-0.15)	-0.003 (-0.54)	0.195 (8.52)***	0.132 (9.25)***	0.738 (128.76)***	0.035 (7.55)***	0.199 (7.54)***	0.612 (16.85)***	0.191 (18.07)***
PCLPX	0.015 (3.79)***	0.037 (8.55)***	-0.005 (-0.33)	-0.04 (-4.25)***	1.038 (262.51)***	0.002 (4.04)***	0.064 (6.89)***	0.903 (62.42)***	0.125 (8.72)***
PCRAX	-0.004 (-0.90)	0.005 (1.10)	0.584 (32.11)***	0.132 (12.78)***	0.832 (191.47)***	0.004 (5.82)***	0.081 (9.79)***	0.898 (100.44)***	0.147 (16.88)***
PCRPX	-0.001 (-0.26)	0.003 (0.54)	0.464 (24.17)***	0.126 (11.13)***	0.821 (168.73)***	0.003 (4.73)***	0.093 (9.07)***	0.892 (87.46)***	0.152 (14.39)***
PDBC	0.005 (0.68)	0.063 (8.13)***	-0.028 (-1.05)	0.027 (1.50)	0.902 (123.02)***	0.007 (4.19)***	0.146 (7.17)***	0.832 (44.92)***	0.178 (8.02)***
PQTIX	0.038 (4.28)***	0.071 (7.24)***	0.037 (1.10)	-0.132 (-6.02)***	0.013 (1.53)	0.02 (4.99)***	0.163 (6.99)***	0.789 (31.24)***	0.213 (10.88)***
PZRMX	0.005 (1.25)	0.097 (25.12)***	0.583 (40.10)***	0.163 (17.81)***	0.212 (54.65)***	0.002 (3.81)***	0.067 (6.42)***	0.904 (61.22)***	0.134 (8.21)***
QMHRX	0.056 (3.33)***	-0.062 (-3.86)***	-0.545 (-9.30)***	-0.294 (-7.69)***	-0.066 (-4.54)***	0.128 (3.37)***	0.095 (4.16)***	0.753 (12.72)***	0.194 (9.42)***
RJI	0.001 (0.11)	0.066 (12.86)***	-0.03 (-1.50)	0.077 (6.57)***	0.87 (180.18)***	0.006 (6.02)***	0.183 (11.05)***	0.792 (49.46)***	0.119 (9.93)***
SKIRX	0.002 (0.47)	0.03 (5.66)***	0.131 (6.97)***	0.096 (9.30)***	0.618 (132.68)***	0.002 (4.50)***	0.128 (11.50)***	0.874 (97.67)***	0.164 (16.70)***
SLV	-0.004 (-0.23)	0.122 (6.70)***	0.814 (11.34)***	1.128 (26.20)***	0.445 (25.39)***	0.022 (3.71)***	0.055 (8.06)***	0.939 (132.39)***	0.213 (12.37)***
VCMDX	0.014 (1.41)	0.013 (1.32)	0.247 (8.13)***	0.259 (9.34)***	0.69 (75.43)***	0.004 (2.40)**	0.11 (4.52)***	0.873 (34.66)***	0.17 (5.37)***
WTMF	-0.001 (-0.11)	-0.008 (-1.11)	0.095 (3.70)***	-0.084 (-5.40)***	0.057 (8.96)***	0.003 (3.38)***	0.059 (6.60)***	0.927 (87.80)***	0.136 (8.42)***

Note: In this table, we estimate a single equation GARCH model to examine the exposure to broad popular indices and commodities-investment products. The model is:

$$R_t = \delta_0 + \delta_1 SPY_t + \delta_2 Bond_t + \delta_3 US\ Treasury_t + \delta_4 DXY_t + \delta_5 SPGSCI_t + \varepsilon_t \quad (2')$$

$$\varepsilon_t|\psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \quad (3')$$

$$\sigma_t^2 = \Omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j} \quad (4')$$

where Rt in the mean equation (equation 2) is the daily return for a particular asset under attention. Equation (3) describes the returns distribution given time-varying conditional variances (Ψt-1 is the information set). The variance equation (4) models the conditional variances as a GARCH(p,q) process where p and q denote the lag length. Ω is the intercept term, αi are ARCH terms, and βj are GARCH terms. We would expect α and β terms to be positive and significant determinants of the returns' conditional variance. The model is estimated assuming t-distribution for the error term with v degrees of freedom (1/TDFI), where TDFI refers to the inverse of the degree of freedom for t-distribution. Suppose the estimated parameter is 0.23. This would imply that the normality assumption is not valid as the degrees of freedom is 4.35 (=1/.23). The assumption of t-distribution corrects for the low degrees of freedom. A significant t-statistics indicates that the normality assumption does not hold. T-statistics are reported in parenthesis.

Table 5: Fama - French (2000-2023)

Asset	Intercept	MKT_rf	SMB	HML	RMW	CMA	ARCH0	ARCH1	GARCH1	TDFI
ABYIX	0.03	0.028	0.034	-0.073	-0.032	0.171	0.074	0.16	0.588	0.201
	(3.16)***	(3.24)***	(2.11)**	(-4.95)***	(-1.49)	(6.02)***	(4.28)***	(4.93)***	(7.85)***	(11.11)***
AHLIX	0.031	-0.001	0.052	-0.098	-0.029	0.193	0.102	0.165	0.575	0.237
	(2.98)***	(-0.10)	(2.93)***	(-6.03)***	(-1.25)	(6.15)***	(4.54)***	(4.44)***	(7.57)***	(13.22)***
AMFNX	0.065	0.056	0.004	-0.106	-0.121	0.348	0.201	0.171	0.536	0.229
	(3.85)***	(4.06)***	(0.16)	(-4.51)***	(-3.37)***	(7.70)***	(4.02)***	(4.19)***	(5.72)***	(11.89)***
AQMRX	0.025	-0.03	-0.004	-0.087	-0.037	0.251	0.063	0.112	0.731	0.186
	(2.19)**	(-2.82)***	(-0.23)	(-4.97)***	(-1.46)	(7.59)***	(3.61)***	(4.26)***	(12.34)***	(10.17)***
ASFYX	0.04	0.131	0.041	-0.155	-0.044	0.314	0.092	0.145	0.701	0.206
	(3.63)***	(11.84)***	(2.07)**	(-8.20)***	(-1.64)	(8.62)***	(5.52)***	(6.26)***	(17.12)***	(16.32)***
BCD	0.024	0.273	-0.045	0.083	-0.2	0.307	0.017	0.079	0.9	0.212
	(1.45)	(17.78)***	(-1.63)	(3.41)***	(-5.50)***	(6.36)***	(2.66)***	(4.71)***	(45.35)***	(7.53)***
BCI	0.015	0.333	-0.067	0.143	-0.306	0.372	0.023	0.097	0.874	0.153
	(0.87)	(21.11)***	(-2.26)**	(5.36)***	(-7.90)***	(6.95)***	(3.20)***	(5.94)***	(44.32)***	(6.11)***
BCSAX	-0.028	0.547	-0.013	0.171	-0.29	0.429	0.006	0.058	0.929	0.108
	(-2.54)**	(48.69)***	(-0.66)	(9.40)***	(-10.79)***	(11.76)***	(3.10)***	(6.79)***	(90.29)***	(6.86)***
BCSKX	0.008	0.543	-0.026	0.174	-0.343	0.478	0.009	0.068	0.915	0.127
	(0.51)	(38.07)***	(-0.98)	(7.83)***	(-10.23)***	(10.45)***	(2.31)**	(4.71)***	(50.84)***	(4.04)***
BRCAX	-0.009	0.245	0.01	0.092	-0.22	0.342	0.007	0.049	0.941	0.13
	(-0.71)	(20.02)***	(0.48)	(4.23)***	(-6.89)***	(7.96)***	(3.11)***	(6.63)***	(108.57)***	(8.52)***
CCOMX	-0.01	0.261	-0.035	0.129	-0.282	0.381	0.007	0.054	0.937	0.121
	(-0.70)	(18.52)***	(-1.48)	(5.62)***	(-8.16)***	(8.18)***	(2.83)***	(6.21)***	(94.32)***	(6.76)***
CCRSX	-0.01	0.261	0.006	0.128	-0.144	0.178	0.005	0.048	0.948	0.119
	(-0.88)	(23.09)***	(0.30)	(6.50)***	(-4.85)***	(4.43)***	(3.00)***	(7.96)***	(150.60)***	(8.86)***
CCSRX	-0.017	0.262	-0.028	0.134	-0.268	0.336	0.009	0.058	0.93	0.12
	(-1.32)	(19.21)***	(-1.19)	(5.87)***	(-7.89)***	(7.34)***	(3.09)***	(6.48)***	(87.61)***	(7.18)***
CMCAX	-0.007	0.303	-0.01	0.199	-0.26	0.259	0.012	0.063	0.92	0.14
	(-0.54)	(24.15)***	(-0.47)	(9.06)***	(-8.52)***	(6.22)***	(3.35)***	(6.72)***	(78.24)***	(8.67)***
CMDY	0.012	0.295	-0.055	0.11	-0.215	0.291	0.015	0.081	0.901	0.176
	(0.63)	(17.81)***	(-1.82)*	(4.23)***	(-5.50)***	(5.40)***	(2.42)**	(4.65)***	(44.49)***	(5.87)***
COM	0.012	0.072	-0.029	0.024	-0.147	0.166	0.006	0.114	0.878	0.203
	(1.11)	(7.87)***	(-1.54)	(1.45)	(-6.35)***	(5.41)***	(2.80)***	(5.77)***	(49.90)***	(7.64)***
COMT	0.017	0.534	-0.1	0.23	-0.502	0.623	0.016	0.086	0.9	0.14
	(1.05)	(31.20)***	(-3.39)***	(8.55)***	(-12.68)***	(12.17)***	(3.21)***	(6.78)***	(64.81)***	(7.85)***
CRSAX	-0.009	0.254	0.011	0.141	-0.119	0.135	0.004	0.045	0.951	0.122
	(-0.77)	(22.65)***	(0.55)	(7.24)***	(-4.02)***	(3.39)***	(2.95)***	(8.10)***	(161.54)***	(9.46)***
DBC	-0.005	0.39	0.004	0.224	-0.199	0.189	0.008	0.056	0.938	0.117
	(-0.35)	(29.38)***	(0.15)	(9.51)***	(-5.82)***	(4.08)***	(3.20)***	(8.29)***	(130.69)***	(9.42)***
DBMF	0.058	0.122	-0.028	-0.044	-0.138	0.368	0.094	0.228	0.67	0.215
	(2.82)***	(6.77)***	(-0.83)	(-1.56)	(-3.45)***	(6.99)***	(3.43)***	(4.19)***	(10.65)***	(8.41)***
DJP	-0.022	0.348	0.007	0.145	-0.151	0.211	0.008	0.05	0.943	0.105
	(-1.72)*	(28.04)***	(0.31)	(6.62)***	(-4.59)***	(4.70)***	(3.37)***	(8.02)***	(135.94)***	(8.15)***
EVOIX	0.041	0.101	-0.045	-0.112	-0.051	0.267	0.036	0.112	0.804	0.161
	(3.91)***	(9.69)***	(-2.42)**	(-6.28)***	(-2.11)**	(7.88)***	(4.58)***	(6.29)***	(27.41)***	(10.19)***
FCSSX	-0.021	0.296	-0.006	0.124	-0.208	0.3	0.016	0.06	0.918	0.14
	(-1.75)*	(24.88)***	(-0.27)	(5.93)***	(-6.76)***	(7.19)***	(4.10)***	(6.92)***	(83.34)***	(14.03)***
FIFGX	0.036	0.353	-0.096	0.144	-0.26	0.315	0.031	0.098	0.869	0.143
	(1.57)	(17.73)***	(-2.58)***	(4.54)***	(-5.64)***	(4.86)***	(2.56)**	(4.48)***	(31.07)***	(4.95)***
GAAVX	0.007	0.109	-0.009	0.068	0.008	0.066	0.01	0.144	0.752	0.203
	(0.99)	(16.66)***	(-0.72)	(6.86)***	(0.53)	(3.51)***	(3.51)***	(4.15)***	(15.93)***	(8.38)***
GCC	0.035	0.448	-0.15	0.313	-0.386	0.315	0.084	0.09	0.823	0.142
	(1.00)	(13.09)***	(-2.67)***	(6.00)***	(-6.36)***	(3.65)***	(2.00)**	(2.98)***	(12.66)***	(3.66)***

Asset	Intercept	MKT_rf	SMB	HML	RMW	CMA	ARCH0	ARCH1	GARCH1	TDFI
GFIRX	0.015	0.118	-0.006	-0.073	-0.015	0.16	0.018	0.163	0.784	0.209
	(1.96)**	(13.74)***	(-0.40)	(-5.26)***	(-0.79)	(6.35)***	(5.32)***	(7.22)***	(32.64)***	(13.34)***
GLD	0.032	0.041	0.032	-0.127	-0.032	0.203	0.008	0.042	0.952	0.184
	(2.51)**	(3.25)***	(1.36)	(-5.99)***	(-1.04)	(4.88)***	(3.24)***	(7.88)***	(161.56)***	(11.84)***
GSG	-0.005	0.474	-0.001	0.294	-0.243	0.214	0.018	0.071	0.92	0.13
	(-0.29)	(29.32)***	(-0.05)	(10.23)***	(-6.10)***	(3.88)***	(3.76)***	(8.76)***	(105.28)***	(9.87)***
JCCSX	0.026	0.525	-0.008	0.254	-0.347	0.374	0.019	0.069	0.904	0.128
	(1.29)	(28.29)***	(-0.25)	(9.36)***	(-8.63)***	(6.83)***	(2.41)**	(4.44)***	(40.71)***	(4.95)***
LACI	0.021	-0.037	0.003	0.011	-0.083	0.06	0.018	0.132	0.86	0.164
	(2.23)**	(-3.80)***	(0.20)	(0.64)	(-3.96)***	(2.14)**	(5.25)***	(11.42)***	(79.16)***	(12.27)***
LCSIX	0.008	-0.012	-0.006	-0.016	-0.022	0.025	0.008	0.113	0.859	0.181
	(1.16)	(-1.57)	(-0.47)	(-1.35)	(-1.43)	(1.13)	(4.18)***	(7.20)***	(49.18)***	(9.13)***
LFMIX	0.032	0.064	0.022	-0.081	0.037	0.171	0.08	0.2	0.582	0.227
	(3.81)***	(7.83)***	(1.42)	(-5.78)***	(1.84)*	(6.22)***	(5.60)***	(6.10)***	(10.30)***	(13.61)***
LOTIX	0.054	0.135	0.019	-0.152	-0.038	0.376	0.297	0.177	0.399	0.188
	(3.58)***	(9.34)***	(0.75)	(-6.59)***	(-1.12)	(8.49)***	(4.90)***	(4.70)***	(3.96)***	(10.96)***
MCSAX	-0.008	0.265	-0.027	0.118	-0.245	0.324	0.027	0.092	0.875	0.164
	(-0.66)	(20.86)***	(-1.18)	(5.41)***	(-7.67)***	(7.53)***	(4.78)***	(7.95)***	(61.30)***	(13.00)***
PCLPX	0.022	0.393	-0.018	0.275	-0.307	0.288	0.019	0.08	0.906	0.16
	(1.47)	(23.99)***	(-0.65)	(9.44)***	(-8.08)***	(5.40)***	(3.63)***	(7.53)***	(76.26)***	(10.45)***
PCRAX	0.01	0.209	0.064	0.178	-0.026	0.014	0.01	0.053	0.939	0.141
	(0.82)	(17.46)***	(2.94)***	(8.47)***	(-0.89)	(0.35)	(4.05)***	(8.75)***	(146.11)***	(13.04)***
PCRPX	-0.008	0.288	-0.001	0.095	-0.185	0.315	0.012	0.063	0.926	0.14
	(-0.59)	(21.69)***	(-0.03)	(4.35)***	(-5.66)***	(7.00)***	(3.91)***	(7.94)***	(108.99)***	(10.45)***
PDBC	0.033	0.414	-0.078	0.213	-0.474	0.594	0.016	0.055	0.93	0.165
	(1.83)*	(22.88)***	(-2.47)**	(7.22)***	(-11.43)***	(10.72)***	(2.82)***	(5.53)***	(74.46)***	(7.83)***
PQTIX	0.037	0.082	0.034	-0.055	-0.028	0.147	0.019	0.169	0.789	0.219
	(4.22)***	(8.46)***	(2.17)**	(-3.76)***	(-1.37)	(5.44)***	(4.99)***	(7.02)***	(31.89)***	(11.16)***
PZRMX	0.006	0.164	0.009	-0.017	-0.038	0.163	0.004	0.078	0.891	0.131
	(0.95)	(27.05)***	(0.84)	(-1.65)*	(-2.60)***	(8.08)***	(3.90)***	(6.87)***	(56.89)***	(6.76)***
QMHRX	0.039	-0.048	-0.01	-0.131	-0.051	0.365	0.136	0.112	0.735	0.184
	(2.24)**	(-2.96)***	(-0.35)	(-5.07)***	(-1.36)	(7.42)***	(3.70)***	(4.45)***	(13.02)***	(9.45)***
RJI	-0.006	0.325	-0.035	0.148	-0.225	0.298	0.003	0.074	0.927	0.131
	(-0.51)	(26.53)***	(-1.59)	(6.83)***	(-7.55)***	(7.40)***	(2.15)**	(8.87)***	(123.12)***	(9.24)***
SKIRX	-0.01	0.243	0.009	0.126	-0.072	0.113	0.006	0.089	0.906	0.138
	(-1.06)	(25.28)***	(0.50)	(7.53)***	(-2.92)***	(3.41)***	(4.36)***	(10.31)***	(117.61)***	(15.07)***
SLV	0.006	0.288	0.102	-0.124	-0.114	0.4	0.02	0.041	0.955	0.224
	(0.26)	(13.90)***	(2.51)**	(-3.38)***	(-2.15)**	(5.58)***	(3.29)***	(7.69)***	(173.82)***	(12.32)***
SPGSCI	0.016	0.26	0.091	0.294	-0.054	-0.004	0.011	0.058	0.936	0.131
	(1.29)	(20.94)***	(4.16)***	(12.92)***	(-1.97)**	(-0.10)	(3.90)***	(9.87)***	(148.72)***	(11.45)***
VCMDX	0.058	0.305	-0.101	0.15	-0.291	0.318	0.029	0.089	0.879	0.142
	(2.33)**	(14.29)***	(-2.65)***	(4.80)***	(-6.09)***	(4.94)***	(2.35)**	(4.17)***	(30.99)***	(4.74)***
WTMF	-0.002	0.002	-0.019	-0.037	-0.111	0.078	0.003	0.058	0.926	0.137
	(-0.28)	(0.39)	(-1.67)*	(-3.19)***	(-6.45)***	(3.52)***	(3.54)***	(6.57)***	(87.09)***	(8.41)***

Note: In this table, we estimate a single equation GARCH model to examine the Fama-French model for all popular indices, LACI, and commodities-investment products. The model is:

$$R_t = \delta_0 + \delta_1 Mkt\_rf_t + \delta_2 SMB_t + \delta_3 HML_t + \delta_4 RMW_t + \delta_5 CMA_t + \delta_6 RMW_t + \varepsilon_t \quad (5')$$

$$\varepsilon_t | \psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \quad (6')$$

$$\sigma_t^2 = \Omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j} \quad (7')$$

where R_t in the mean equation (equation 5') is the daily return for a particular asset under attention. Fama-French factors are already defined. δ_1 .. δ_6 are factor betas. The model is estimated assuming t-distribution for the error term. We assume t-distributed errors with v degrees of freedom (1/TDFI), where TDFI refers to the inverse of the degree of freedom for t-distribution. A significant t-statistics indicates that the normality assumption does not hold. T-statistics are reported in parenthesis. The Fama-French factors are as follows (reproduced from Ken French's website): "Rm-Rf, the excess return on the market, value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates), SMB (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios, HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, CMA (Conservative Minus Aggressive (firms that invest aggressively)) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios." Conservative represents firms that invest conservatively.

Table 6: Cointegration between LACI and Competing Products

Asset	2000-2023	2000-2004	2005-2009	2010-2014	2015-2019	2020-2023
SPGSCI	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
SPY	Not cointegrated	Not cointegrated	Not cointegrated	Cointegrated	Not cointegrated	Not cointegrated
BOND	Cointegrated	Cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
US TREASURY	Cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
MUNI	Not cointegrated	Cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
DXY	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
ABYIX	Not cointegrated	Fund did not exist	Fund did not exist	Cointegrated	Not cointegrated	Not cointegrated
AHLIX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
AMFNX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
AQMRX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
ASFYX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
BCD	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
BCI	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
BCSAX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
BCSKX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
BRCAX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
CCOMX	Not cointegrated	Fund did not exist	Fund did not exist	Cointegrated	Not cointegrated	Not cointegrated
CCRSX	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
CMCAX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
CMDY	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
COM	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
COMT	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
CRSAX	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
DBC	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
DBMF	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
DJP	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
EVOIX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated

Asset	2000-2023	2000-2004	2005-2009	2010-2014	2015-2019	2020-2023
FCSSX	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
FIFGX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
GAAVX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
GCC	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated
GFIRX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
GIFMX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
GSG	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
JCCSX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
LCSIX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
LFMIX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
LOTIX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
MCSAX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
PCLPX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
PCRAX	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
PCRPX	Cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
PDBC	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
PQTIX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
PZRMX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
QMHRX	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
RJI	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
SKIRX	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
SLV	Not cointegrated	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated	Not cointegrated
VCMDX	Not cointegrated	Fund did not exist	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated
WTMF	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
WTMF	Not cointegrated	Fund did not exist	Fund did not exist	Not cointegrated	Not cointegrated	Not cointegrated
Cointegrated /Not-cointegrated	3/52	2/7	0/17	3/39	0/51	0/52

Table 7: Herding and LACI (1993-2021)

CSAD (2000-2023)

Asset	Intercept	com_csad_l	fx_csad_f	ARCH0	ARCH1	GARCH1	TDFI
ABYIX	0.007	0.013	0.001	0.086	0.165	0.544	0.197
	(0.30)	(0.72)	(1.33)	(4.34)***	(4.87)***	(6.55)***	(11.10)***
AHLIX	0.011	0.013	0.001	0.099	0.164	0.591	0.239
	(0.42)	(0.65)	(0.74)	(4.55)***	(4.48)***	(8.13)***	(13.11)***
AMFNX	0.04	0.003	0.002	0.211	0.156	0.545	0.231
	(0.92)	(0.10)	(1.57)	(3.90)***	(4.02)***	(5.68)***	(11.79)***
AQMRX	-0.021	0.018	0.001	0.027	0.08	0.855	0.195
	(-0.74)	(0.81)	(1.59)	(3.32)***	(4.53)***	(27.50)***	(10.42)***
ASFYX	0.015	0.014	0.001	0.137	0.124	0.646	0.211
	(0.53)	(0.66)	(1.77)*	(5.08)***	(5.43)***	(11.34)***	(15.90)***
BCD	-0.024	0.058	-0.001	0.009	0.074	0.924	0.242
	(-0.53)	(1.78)*	(-0.89)	(1.97)**	(4.65)***	(65.84)***	(7.96)***
BCI	-0.047	0.066	0	0.02	0.088	0.896	0.17
	(-0.93)	(1.69)*	(-0.13)	(2.77)***	(5.50)***	(51.71)***	(6.29)***
BCSAX	-0.014	0.028	-0.001	0.007	0.064	0.929	0.127
	(-0.42)	(1.21)	(-0.65)	(2.91)***	(7.49)***	(105.18)***	(8.10)***
BCSKX	-0.02	0.052	0	0.013	0.077	0.914	0.14
	(-0.36)	(1.16)	(0.04)	(2.22)**	(5.27)***	(60.42)***	(5.20)***
BRCAX	-0.025	0.037	-0.001	0.007	0.048	0.943	0.138
	(-0.79)	(1.57)	(-1.47)	(3.05)***	(7.02)***	(119.32)***	(9.45)***
CCOMX	-0.03	0.029	0	0.007	0.055	0.938	0.131
	(-0.86)	(1.16)	(-0.44)	(2.66)***	(6.39)***	(101.79)***	(7.14)***
CCRSX	-0.016	0.027	-0.001	0.005	0.05	0.947	0.128
	(-0.54)	(1.23)	(-0.81)	(2.82)***	(8.29)***	(154.86)***	(9.46)***
CCSRX	-0.031	0.029	-0.001	0.008	0.057	0.934	0.14
	(-0.92)	(1.25)	(-0.67)	(2.91)***	(6.58)***	(98.39)***	(7.88)***
CMCAX	-0.014	0.026	-0.001	0.008	0.054	0.938	0.157
	(-0.42)	(1.18)	(-0.74)	(2.95)***	(6.75)***	(107.99)***	(9.36)***
CMDY	-0.023	0.039	0	0.008	0.08	0.919	0.221
	(-0.45)	(1.03)	(0.11)	(1.82)*	(4.71)***	(60.85)***	(6.75)***
COM	-0.044	0.046	0.001	0.004	0.127	0.879	0.224
	(-1.66)*	(2.30)**	(0.77)	(2.45)**	(5.87)***	(55.27)***	(7.80)***
COMT	-0.041	0.062	0.001	0.028	0.091	0.892	0.157
	(-0.80)	(1.49)	(0.62)	(3.25)***	(6.44)***	(56.88)***	(7.92)***
CRSAX	-0.008	0.022	-0.001	0.005	0.05	0.947	0.129
	(-0.29)	(1.07)	(-0.87)	(2.85)***	(8.61)***	(161.84)***	(9.82)***
DBC	0.013	0.018	-0.001	0.007	0.057	0.94	0.126
	(0.36)	(0.69)	(-1.11)	(2.86)***	(8.59)***	(139.21)***	(9.74)***
DBMF	0.029	0.027	0.001	0.087	0.2	0.71	0.22
	(0.56)	(0.63)	(0.59)	(3.19)***	(4.03)***	(11.87)***	(8.44)***
DJP	-0.02	0.025	-0.001	0.007	0.053	0.943	0.112
	(-0.58)	(1.01)	(-0.82)	(3.04)***	(8.41)***	(143.19)***	(8.43)***
EVOIX	0.006	0.018	0.002	0.047	0.118	0.777	0.16
	(0.22)	(0.97)	(1.95)*	(4.75)***	(6.29)***	(23.39)***	(10.05)***
FCSSX	-0.022	0.021	0	0.011	0.056	0.933	0.155
	(-0.68)	(0.90)	(-0.35)	(3.67)***	(7.15)***	(108.29)***	(14.07)***
FIFGX	0.021	0.049	0	0.028	0.09	0.888	0.163
	(0.33)	(0.98)	(-0.25)	(2.41)**	(4.58)***	(39.50)***	(5.14)***
GAAVX	0.01	0.006	0	0.013	0.194	0.718	0.208
	(0.49)	(0.36)	(0.72)	(3.42)***	(4.69)***	(13.95)***	(7.41)***

Asset	Intercept	com_csad_l	fx_csad_f	ARCH0	ARCH1	GARCH1	TDFI
GCC	-0.052	0.117	0.001	0.139	0.093	0.803	0.156
	(-0.49)	(1.23)	(0.27)	(1.93)*	(2.67)***	(10.28)***	(4.14)***
GFIRX	0.044	-0.016	0.001	0.031	0.166	0.734	0.204
	(2.25)**	(-1.21)	(1.12)	(5.57)***	(6.59)***	(23.05)***	(13.49)***
GLD	0.064	-0.008	-0.001	0.008	0.043	0.952	0.188
	(1.89)*	(-0.32)	(-0.88)	(3.26)***	(7.85)***	(160.19)***	(12.00)***
GSG	0.038	0.009	-0.001	0.014	0.065	0.931	0.132
	(0.87)	(0.27)	(-1.11)	(3.20)***	(8.81)***	(124.55)***	(9.92)***
JCCSX	0.009	0.048	0	0.029	0.067	0.909	0.147
	(0.13)	(0.88)	(-0.17)	(2.42)**	(4.48)***	(46.79)***	(5.26)***
LACI	**0.054**	**-0.02**	**-0.001**	**0.018**	**0.133**	**0.86**	**0.167**
	(2.30)**	**(-1.03)**	**(-0.95)**	**(5.24)*****	**(11.43)*****	**(79.15)*****	**(12.37)*****
LCSIX	-0.008	0.009	0.001	0.007	0.112	0.862	0.182
	(-0.47)	(0.73)	(1.13)	(4.14)***	(7.28)***	(50.75)***	(9.19)***
LFMIX	0.003	0.018	0.001	0.085	0.197	0.57	0.222
	(0.12)	(1.16)	(1.66)*	(5.66)***	(6.10)***	(9.83)***	(13.50)***
LOTIX	0.041	-0.004	0.002	0.3	0.172	0.412	0.179
	(1.09)	(-0.13)	(2.09)**	(4.95)***	(4.79)***	(4.24)***	(10.91)***
MCSAX	-0.011	0.024	-0.001	0.025	0.09	0.886	0.178
	(-0.33)	(1.02)	(-0.86)	(4.58)***	(7.92)***	(68.76)***	(13.15)***
PCLPX	0.065	0.006	-0.001	0.013	0.07	0.925	0.182
	(1.60)	(0.20)	(-1.48)	(3.11)***	(7.55)***	(102.38)***	(11.10)***
PCRAX	0.022	0.018	-0.001	0.011	0.06	0.933	0.148
	(0.71)	(0.80)	(-1.16)	(3.90)***	(9.38)***	(142.09)***	(13.56)***
PCRPX	-0.017	0.029	-0.001	0.01	0.065	0.929	0.147
	(-0.51)	(1.21)	(-0.63)	(3.53)***	(8.25)***	(117.81)***	(10.69)***
PDBC	-0.025	0.049	0.001	0.026	0.062	0.92	0.166
	(-0.47)	(1.09)	(0.65)	(2.82)***	(5.39)***	(63.22)***	(7.89)***
PQTIX	0.005	0.018	0.001	0.024	0.161	0.778	0.217
	(0.21)	(1.13)	(1.83)*	(5.05)***	(6.69)***	(28.26)***	(11.23)***
PZRMX	-0.02	0.027	0	0.002	0.07	0.918	0.154
	(-1.27)	(2.43)**	(0.46)	(3.45)***	(7.27)***	(85.69)***	(8.72)***
QMHRX	-0.035	0.029	0.002	0.071	0.092	0.833	0.19
	(-0.81)	(0.89)	(1.49)	(3.49)***	(4.73)***	(24.31)***	(9.85)***
SKIRX	-0.021	0.021	0	0.004	0.08	0.918	0.15
	(-0.91)	(1.26)	(0.02)	(3.69)***	(10.01)***	(130.66)***	(13.64)***
SLV	0.04	0.002	0	0.017	0.04	0.958	0.227
	(0.70)	(0.05)	(-0.22)	(3.05)***	(7.80)***	(187.76)***	(12.67)***
SPGSCI	0.064	-0.005	-0.002	0.01	0.056	0.939	0.13
	(2.06)**	(-0.20)	(-2.11)**	(3.64)***	(9.95)***	(159.40)***	(11.39)***
VCMDX	0.03	0.057	0	0.031	0.1	0.876	0.165
	(0.46)	(1.03)	(-0.14)	(2.33)**	(4.29)***	(33.33)***	(4.80)***
WTMF	-0.012	0.009	0	0.003	0.06	0.924	0.131
	(-0.72)	(0.78)	(-0.13)	(3.50)***	(6.69)***	(85.84)***	(8.20)***

We estimate commodities-specific herding using the cross-sectional absolute standard deviations (CSAD) method. We assume that the SPGSCITR is the appropriate benchmark in this paper. The CSAD measure is:

$$CSADt = \frac{1}{N}\sum_{i=1}^{N} |ri,t - rm,t| \quad (11)$$

where $r_{i,t}$ are the daily returns from a particular commodity, and the $r_{m,t}$ is the daily return from the market index (SPGSCITR). We then calculated a weighted aggregate herding measure for all commodities by their respective weights in LACI. The GARCH model for an asset is:

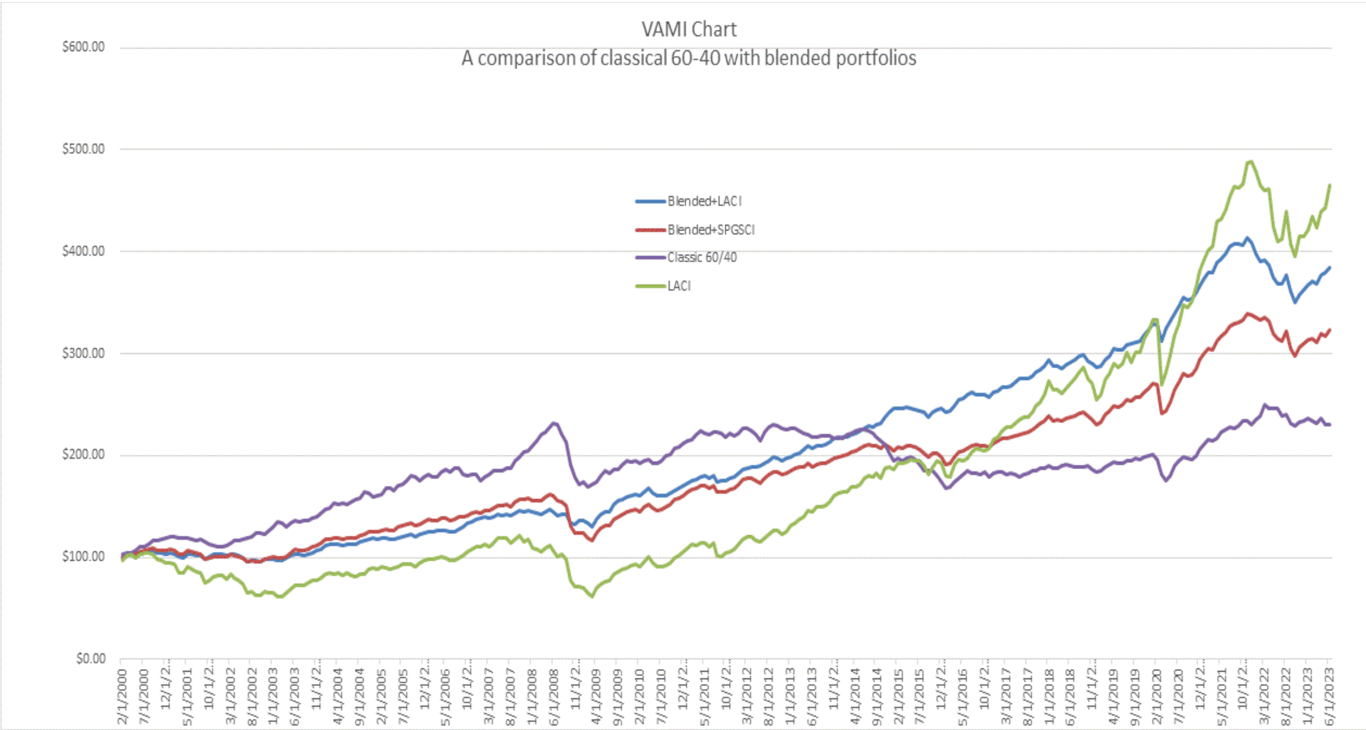
$$R_t = \delta_0 + \delta_1 CSAD_{COM,t} + \delta_2 CSAD_{FX,t} + \varepsilon_t \quad (12)$$

$$\varepsilon_t|\psi_{t-1} \sim \mathrm{N}(0, \sigma_t^2) \quad (13)$$

$$\sigma_t^2 = \Omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j} \qquad (14)$$

R_t in the mean equation (equation 12) is the daily returns from the asset under consideration. $CSAD_{COM,t}$ is the aggregate herding measure in the commodities market. Similarly, $CSAD_{FX,t}$ denotes herding in the currency market using the following bilateral major exchange rates (GBP, Euro, JPY, CAD, CHF, Skr) vis-à-vis the US dollar. The model is estimated assuming t-distribution for the error term.

Table 8



SPY is the SPDR S&P 500 ETF Trust
LACI is the Liquid Alternative Commodity Index - Total Return
SPGSCITR is the S&P Goldman Sachs Commodity Index - Total Return
Balanced portfolio includes SPY, Bloomberg US Aggregate Bond Index, and LACI

Performance

Statistics	**Monthly**	**Annualized**
Portfolio return	0.49%	5.91%
Risk	1.53%	5.31%
Risk-free rate	0.20%	2.44%
Sharpe	0.189	0.653021
Average Excess Return	0.055%	
Tracking error	1.009%	
Information ratio	5.461%	
Downside risk	0.00248%	
Beta	0.678169764	
Number of up months	190	
Number of down months	91	
Manager upside capture	0.87	
Manager downside capture	0.65	
Capture Ratio	1.34	

Statistics	Blended+l	Blended+:	Classic 60-40	SPY
Average Annual Return	5.910%	5.248%	3.809%	7.191%
Standard Deviation	5.314%	6.682%	6.777%	17.667%
Sharpe	0.6530	0.4203	0.2020	0.2689
Max Drawdown	-5.947%	-12.571%	-10.336%	-20.515%

Appendix A: Multivariate GARCH Model of Time-Varying Correlation

We estimate time-varying correlation using a multivariate (4 equations) GARCH model. This is in response to preliminary analysis that suggested that returns are not normally distributed. Therefore, unconditional correlation cannot represent the dynamic evolution of the correlation coefficient over time. The multivariate GARCH model is used that permits temporal variation of the conditional univariate and multivariate distribution of the asset returns. To illustrate, we show a bivariate conditional distribution of a pair of asset returns which can be parameterized with the following GARCH model (see, for example, Kroner and Sultan (1993)):

$$\begin{aligned} \Delta Ri_t &= \alpha_0 + \varepsilon_i \\ \Delta Xi_t^* &= \beta_0 + \varepsilon_i^* \end{aligned} \tag{A1}$$

$$\begin{bmatrix} \varepsilon_i \\ \varepsilon_{i^*} \end{bmatrix} |\psi_{t-1} \sim D(0, H_t) \tag{A2}$$

$$H_t = \begin{bmatrix} h_{i,t} \\ h_{ii^*t} \\ h_{i^*,t} \end{bmatrix} = \begin{bmatrix} \tau_i \\ \tau_{ii^*} \\ \tau_{i^*} \end{bmatrix} + \begin{bmatrix} a_{11} a_{12} a_{13} \\ a_{21} a_{22} a_{23} \\ a_{31} a_{32} a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t-1}^2 \\ \varepsilon_{i,t-1}\varepsilon_{i^*,t-1} \\ \varepsilon_{i^*,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} b_{12} b_{13} \\ b_{21} b_{22} b_{23} \\ b_{31} b_{32} b_{33} \end{bmatrix} \begin{bmatrix} h_{i,t-1} \\ h_{ii^*,t-1} \\ h_{i^*,t-1} \end{bmatrix} \tag{A3}$$

where ΔRi_t and ΔXi^*_t in the mean equations (A1) are returns of a pair of assets that may be correlated. Equation (A2) describes the joint density functions. In equation (A3), $h_{i,t}$ ($h_{i^*,t}$) is the conditional variance of the returns (say, SPGSCITR and SPY) and ε_i and ε_{i^*} are the residuals from the mean equations (A1). In equation (A3), τs are constant terms in H_t, $a_{ij}$are ARCH coefficients, and $b_{ij}$are GARCH coefficients. The off-diagonal elements of the ARCH and GARCH matrices are helpful in understanding volatility transmission between these two interest rates. For example, the coefficient a_{12} measures the response of the volatility of the SPGSCI to innovations in the SPY. However, there are nine parameters to be estimated (in our case, we have 16 ARCH parameters and 16 GARCH parameters given a six-equations model). To avoid convergence problems and economize on the number of parameters, [a] and [b] matrices are assumed to be block-diagonal:

$$H_t = \begin{bmatrix} h_{i,t} \\ h_{ii^*t} \\ h_{i^*,t} \end{bmatrix} = \begin{bmatrix} \tau_i \\ \tau_{ii^*} \\ \tau_{i^*} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t-1}^2 \\ \varepsilon_{i,t-1}\varepsilon_{i^*,t-1} \\ \varepsilon_{i^*,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} h_{i,t-1} \\ h_{ii^*,t-1} \\ h_{i^*,t-1} \end{bmatrix} \tag{A4}$$

This specification implies that the volatilities are determined by the lagged squared residuals as well as past volatilities. The estimated H_t matrix offers convenient ways to capture the intricate and dynamic relationship between these assets. For example, the dynamic hedge ratio (Ω_t) can be easily solved from the following equation:

$$\Omega_t = \frac{h_{ii^*,t}}{h_{i^*,t}} \tag{A5}$$

where $h_{ii^*,t}$ is the time-varying covariance between changes in i and i*, and $h_{i^*,t}$ is the time-varying conditional variance of i*. The time-dependent hedge ratios utilize the conditional variance/covariance as opposed to the traditional hedge ratio based on unconditional estimates of the variance/covariance. From equation (A4), one can also derive:

$$\rho_t(i, i^*) = \frac{h_{ii^*,t}}{\sqrt{(h_{i,t} * h_{i^*,t})}} \tag{A6}$$

We estimate 6 correlations between the assets and subscript t shows how their correlations evolve.