Financial Analysts Journal

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ufaj20

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**To cite this article:** Philippe Jorion (2021): Hedge Funds vs. Alternative Risk Premia, Financial Analysts Journal, DOI: 10.1080/0015198X.2021.1960133

**To link to this article:** https://doi.org/10.1080/0015198X.2021.1960133



Published online: 06 Sep 2021.

**Financial Analysts Journal** | A Publication of **CFA Institute**
https://doi.org/10.1080/0015198X.2021.1960133

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Research

# Hedge Funds vs. Alternative Risk Premia

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**Alternative risk premia (ARP) are designed to provide low-cost exposures to long–short risk premia often embedded in hedge fund returns. This article describes the performance of the ARP market in the form of bank-provided total return swaps, which are investable strategies that provide after-cost access to ARP. Over the 2010–20 period, many of these risk premia provided significantly positive returns. In addition, these ARP explain a high fraction of returns on hedge fund indexes, especially for quantitative strategies, along with traditional market factors. Finally, we find that ARP and market factors largely eat away hedge fund index returns.**



**Disclosure:** The author reports no conflicts of interest.

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Passive management has transformed the asset management industry. The first index fund was started in 1972. Since then, the US index mutual fund industry has grown to more than $4 trillion, which represents 24% of the industry's assets under management. This growth was driven by skepticism about the value of active management and a relentless search for lower fees.

The next wave of innovation was the emergence of "factor-based" funds, sometimes called "smart," "strategic," or "dynamic" beta. These funds sit between active and passive management by following preset investment rules. They also charge less than active funds by implementing automated quantitative strategies that eschew security-specific analysis. Initially, these funds focused mainly on long equities—for example, by tilting the portfolio toward cheap, value stocks. The hope was that such strategies would generate a "risk premium" or positive long-term return because of some behavioral anomaly or institutional constraint.

Alternative risk premia (ARP) funds represent the next logical step. These funds take both long *and* short positions to navigate within and across asset classes. Such flexibility is the domain of hedge funds. Indeed, ARP funds aim to replicate some of the returns of hedge funds by using automated trading rules. ARP funds are also attractive because of their lower costs relative to hedge funds; management fees are typically below 1% compared with management fees of around 2% for hedge funds, on top of their incentive fees. In addition, ARP funds have better liquidity than hedge funds, often with daily redemption schedules rather than monthly or longer schedules followed by most hedge funds, which can also have lockups. For these reasons, ARP funds are often called "liquid alternatives."

ARP investments are starting to be widely available and can be accessed through two channels. The first consists of private funds offered by asset managers to institutional investors, plus a limited range of UCITS (undertakings for the collective investment in transferable securities) funds. The second consists of risk premia products offered by banks (also called "broker/dealers") in the form of total return swaps (TRS), which is a relatively new market available to institutional investors. The purpose of this article is to provide the first analysis of this bank risk premia (BRP) market and to compare its performance with that of hedge funds.

This market has expanded rapidly; **Table 1** describes its current size. According to Albourne (2020), the total market amounted to $704 billion in notional amount at the end of 2019.[1] This amount is split about equally between asset managers and banks. Table 1 also shows a typical count of products within each asset class for bank products.

This article focuses on the performance of bank products, for several reasons. First, these bank TRS give direct access to ready-made alternative risk premia. This market is very large, currently around $360 billion, with perhaps 20 active banks and thousands of products. Little empirical research has been published on it.[2] Yet, this market is attracting interest. Indeed, the Standards Board for Alternative Investments (SBAI), an industry association, recently issued two "best practices" reports (SBAI 2020a; SBAI 2020b) on broker/dealer products covering product selection and backtesting.

Second, this market created access to a finely detailed set of risk premia across many asset classes and styles. This information should prove useful for understanding—even replicating—some hedge fund returns. Indeed, Fung and Hsieh (2004), who provided a seminal approach to explaining hedge fund returns in terms of only seven factors also surmised, "Research on additional hedge fund styles will probably discover other risk factors" (p. 71). The bank ARP market indeed provides a systematic way to explore additional risk factors and to sort through what has been called the "risk factor zoo."[3]

Third, academic research on hedge funds has used factor returns computed without accounting for trading costs, borrowing costs, or market impact.[4] This approach unfairly penalizes the performance evaluation of hedge funds because missing transaction costs generate artificially low alphas. In contrast, returns on bank products represent actual net flows to investors, so they necessarily account for all these costs. This accounting is essential for strategies such as trend, in which turnover can be very high, or when shorting single stocks, which can be quite expensive.

This focus on the performance of bank products is in line with recent work on mutual funds arguing that omitting transaction costs in benchmarks or factor returns creates a downward bias for measures of skill in performance evaluation.[5]

For this analysis, I used a hitherto-unexplored data source consisting of BRP indexes constructed by Hedge Fund Research (HFR). These indexes aggregate some 1,100 bank products, providing good coverage of this space. This study evaluated the performance of such bank ARP products and compared them with hedge funds for the 2010–20 period.[6] I expected ARP products to explain returns for hedge funds that followed quantitative strategies but to do so less for funds that focused on security-specific analysis. These results should be of interest to investors contemplating investments in ARP and in hedge funds.

## Risk Premia, Fees, and Net Alpha

Hedge fund investors are motivated by the view that hedge funds can produce alpha with a risk level substantially lower than traditional long equities. Many investors balk at the fees charged by the

**Table 1. Size of the Risk Premia Market**

| | Equities | Rates | Credit | Currencies | Commodities | Multiasset | Total |
|---|---|---|---|---|---|---|---|
| *Notional amount invested ($ billions)* | | | | | | | |
| Banks | $131 | $40 | $6 | $17 | $88 | $78 | $360 |
| Asset managers | $181 | $43 | $20 | $5 | $9 | $86 | $344 |
| *HFR bank indexes* | | | | | | | |
| Number of products | 591 | 97 | 42 | 82 | 249 | 64 | 1,125 |

*Notes*: The top rows show the market size estimated by Albourne (2020) as of December 2019. The market is split between bank products and asset managers. The bottom row reports the number of bank products in each asset class index, as reported by Hedge Fund Research in 2018. In comparison, LuxHedge reported that the alternative UCITS market has approximately 1,400 funds with a total of $430 billion in assets under management.

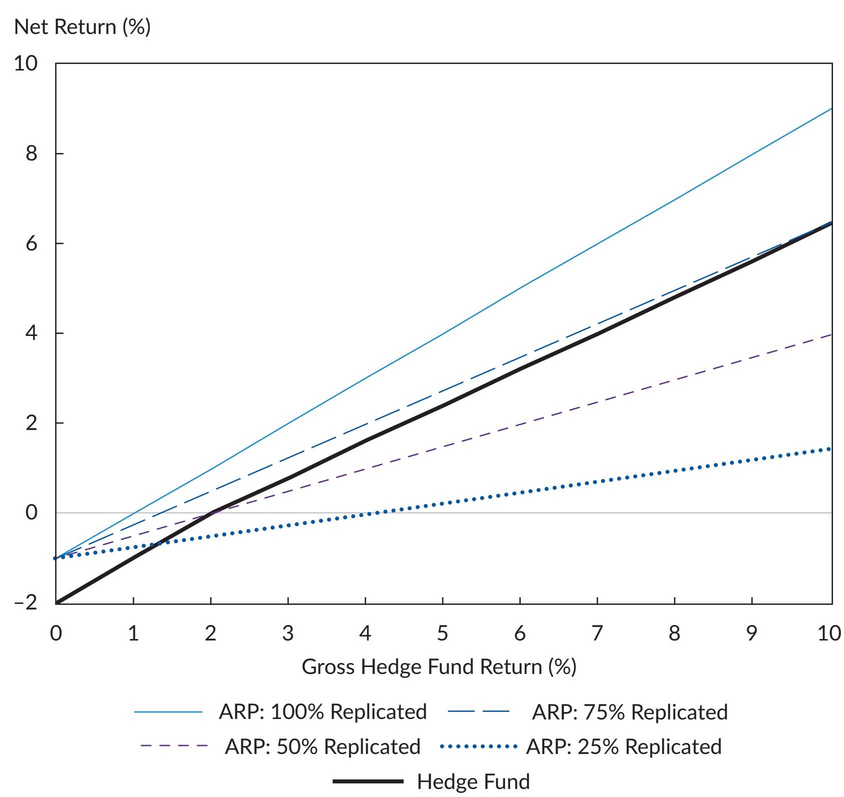
industry, however, even though what ultimately matters are *net* returns. The traditional model calls for 2% fixed management and 20% incentive fees. In practice, these fees have gone down steadily over time and are now at 1.4% and 18.4%, respectively.[7] Even so, such fees represent a major drag on gross performance.

The question is whether ARP investments can provide a good approximation to hedge fund returns. On the one hand, one should expect that the average ARP fund can provide only a fraction of the gross return for a hedge fund with the same broad strategy. For example, a long–short equity hedge fund can devote more resources to the portfolio management process, where value added is created from both stock selection and factor exposure. Let us call this fractional replication an "efficiency" ratio of, say, *r* = 50%. On the other hand, the ARP fund benefits from charging a lower management fee—say, 1% flat. The question is, what is the net of these two effects, efficiency versus fees?

To illustrate, **Figure 1** shows *net* returns for the two approaches, hedge funds and ARP funds, for various levels of gross hedge fund returns and replication ratios. On the one hand, with perfect replication, *r* = 100%, the ARP fund must dominate as a result of lower fees. This situation is unlikely because it would quickly lead to the demise of hedge funds. Even with an imperfect replication of *r* = 75%, however, the ARP fund still dominates for the entire range of gross returns up to 10%. On the other hand, with *r* = 50%, the hedge fund dominates in the range of gross returns above 2%. For a gross return of +10%, for example, the net returns are 6.4% versus 4.0% for, respectively, the hedge fund and ARP fund. At the other extreme, at *r* = 25% or below, the ARP fund becomes totally uncompetitive. So, the comparison hinges on the replication ratio. The empirical analysis later will show that correlation coefficients, estimates of this ratio, are on the order of 50% for some hedge fund categories.

Over multiple horizons, the effect of incentive fees is much more complex, and much worse,

**Figure 1.** Comparison of Net Returns for Hedge Funds and ARP Funds




*Notes*: Net performance of hedge funds and ARP funds are compared for various levels of gross-of-fees returns over one year. The typical hedge fund is assumed to carry a management fee of 2% and an incentive fee of 20%. The ARP fund has a fixed management fee of 1%. Comparative numbers are presented for various assumptions about the fraction of hedge fund gross returns that can be replicated by the ARP fund, varying from 100% (perfect replication) down to 25%.

than depicted in Figure 1. For the manager, these fees are equivalent to long option positions that crystallize profits at regular intervals, typically annually. As a result, because the investor is short convexity, large variations in annual returns lower average annual net returns.

As a simplified example, consider a two-year horizon with gross return of +30% in the first year followed by –10% in the second year. The average annual gross return is still +10%. The net returns on the hedge fund are then +22.4% and –12%, averaging to +5.2%, lower than the previous 6.4% because of convexity. The ARP return, however, is still at 4.0%. So, the difference is now halved, from 2.4% to 1.2%. Admittedly, this effect is mitigated by high-water marks. Even so, underwater funds are more likely to close, which partially defeats the purpose of high-water marks. This asymmetry worsens the comparative advantage of hedge funds.[8]

Finally, hedge fund managers seldom use hurdle rates to set fees. Returns are not adjusted for any directional equity risk nor, for that matter, for the risk-free rate. As a result, some of the incentive fee may provide compensation for the equity premium.

## Alternative Risk Premia as Bank Products

ARP strategies can be implemented in a few ways. Many hedge fund managers offer pure ARP funds as part of their suite of products, either in the traditional hedge fund commingled format or as separate accounts—or even as the UCITS-compliant funds that are offered to the public in Europe.[9]

Recently, banks have been offering total return swaps to access risk premia strategies directly. The investor receives the total return on the trading strategy in exchange for paying a floating rate plus a swap spread. No upfront payment is required for the notional, so these products are "unfunded."

**Bank Swaps.** Such TRS are an extension of the OTC swap market, which started in the early 1980s as currency or interest rate swaps. Later, the market was extended to swaps paying or receiving the total return on an index, such as the S&P 500 Index, which is constructed by a third party.

The use of swaps has widened since the 1980s. Asset managers use TRS to implement their equity trading strategies through so-called basket swaps, in which the fund manager chooses the positions. Such TRS can be viewed as "outsourced" execution, or trading, desks. As usual, the choice to outsource or not largely depends on which structure is most cost efficient.

**Bank Risk Premia Swaps.** Bank ARP products represent the next step, strategies in which both the trading algorithm and execution are outsourced to the bank. For this outsourcing, the return on the trading strategy must be precisely defined in a "rule book"—a confidential, often lengthy, document explaining the precise details of the trading strategy so that it can be exactly reproduced. Valuation is typically carried out using closing prices, from exchanges or third parties, and applying fixed, prespecified transaction costs. This process leads to a time series of daily "benchmark" TRS prices that can be used for mark-to-market valuation and for entering or exiting the product. Ideally, the construction of the benchmark follows the principles of the International Organization of Securities Commissions (IOSCO).[10] Such products typically offer daily liquidity.

No industry standards have been set for such bank products, unfortunately. Generally, three sources of costs should be considered: (1) costs that are embedded in the index, (2) external swap fees, and (3) entry and exit costs. Banks can profit from charging transaction costs that are higher than actual direct trading costs. They also profit from the "external" swap spread, which covers financing as well as a reward for the banks' intellectual property. Such spreads typically vary from 0 bps to 100 bps, depending on the product. Banks do list a "stated" spread, but it can usually be negotiated. In some cases, however, the swap fee is embedded in the product return. Therefore, a careful accounting of all costs is required when comparing products.

Banks have a comparative advantage in offering such products because the transaction flows from these TRS go into their trading books and may be crossed against other trades, so they do not bear all actual trading costs. Similarly, trading-intensive strategies, such as daily rehedging of options or intraday trading, can be done efficiently within bank trading books.

Access to such TRS is subject to setup costs, as with any OTC swap. Indeed, the client needs to establish a separate International Swaps and Derivatives Association agreement for each counterparty bank and post initial margin. Because the margin earns the short-term risk-free rate (i.e., Fed funds rate), the opportunity cost is very low. As usual, the swap is subject to marking-to-market requirements. Such cash flows entail ongoing operational costs. In addition, enough cash should be kept to meet the most stringent margin calls. Finally, any swap is subject to counterparty risk, meaning that the bank could default, potentially leading to the loss of the posted margin and unpaid gains.

Next, note that investors can only *receive* the return on these trading strategies. This limitation is unlike traditional bank swaps, such as those on the S&P 500, where investors can either receive or pay the return on the index, albeit at different swap spreads.

ARP are generally classified into categories by asset class (equity, interest rates, credit, currency, commodity, and multiasset) and by investment style (carry, momentum/trend, value, volatility, multistyle).[11] Even within each category, implementation often varies widely as banks compete by trying to differentiate themselves from others. Equity value products, for instance, can be built within or across countries and sectors. They are usually long individual stocks but often hedge with index futures instead of single names. Products can also differ in terms of their inputs or signals, parameters, portfolio construction, and risk control. These differences can lead to wide variations in returns within categories.

## Bank Risk Premia Indexes

This section examines issues that may arise with bank product data for ARP investing and then considers HFR bank systematic risk premia indexes.

**Issues with Bank Product Data.** Even though this market is large and expanding, its decentralized nature makes compiling systematic information on the performance of these bank products difficult. Many banks list their products on Bloomberg but often with restricted access. Even if a product is listed, no information is given on swap fees or whether transaction costs are embedded. In addition, characteristic data, such as the "live date" and product description, are not easily accessible.

Furthermore, because TRS are unfunded products, they can easily embed various levels of leverage. As a result, banks frequently offer the same product with varying levels of target volatility—for example, 5% and 10%. Consequently, the same profit/loss can be achieved by investing $2 million and $1 million in, respectively, those two products, one of which is thus economically redundant. Thus, for product evaluation, only one product should be selected. In addition, because volatility can vary widely for products in the same category across banks, comparisons should adjust for volatility. An investor can focus on Sharpe ratios or, more intuitively, the annual average excess return, $\bar{R}$, adjusted to a target volatility level of, say, 10%. This approach also applies to measured alpha. Similarly, the investor can focus on correlations instead of slopes such as beta coefficients.

In addition, TRS data are subject to many of the biases also observed with commercial databases of hedge funds. These biases include the "backfill" and "survivorship" biases. The backfill bias occurs because hedge fund managers can choose whether and when to list their funds. Because listing is voluntary, backfilled returns tend to be higher than nonbackfilled returns. This bias can be controlled by using returns only after the listing date, as suggested by Jorion and Schwarz (2019). Note that hedge fund databases include only actual fund returns; simulated returns are inadmissible. The survivorship bias occurs because hedge funds are more likely to close after a period of underperformance. This bias is controlled by keeping a record of live and dead funds in databases.

Such biases are normally avoided for hedge fund indexes that are constructed from live returns. The backfill bias is avoided because only current fund returns are included. The survivorship bias is lessened because funds that close are still included in the index history, hopefully with the last returns.

Similar issues arise with bank products. First, most such products are "backtested" with historical data, presumably in a search for an investment rule that produces good results. Such data are susceptible to biases arising from data mining, which is the focus of an increasing body of research.[12] The algorithm is frozen at some point, however, which becomes the "live date." As with nonbackfilled data for hedge funds, bank product returns are likely to be more realistic after the live date. Suhonen, Lennkh, and Perez (2017) found that alphas are reduced by half in the live period.[13]

Second, products that perform poorly are likely to be dropped from the bank's current lineup and perhaps replaced by better-performing versions. This issue is more difficult to deal with than data mining and requires keeping track of dead products.[14] As in the case of hedge funds, however, indexes of live bank products should be less affected.

**HFR BRP Indexes.** In June 2018, HFR launched the "HFR Bank Systematic Risk Premia Indices." These indexes are designed to track the performance of bank risk premia products in various categories—that is, asset classes and styles based on a large sample of products, approximately 1,125 products offered by 12 major banks. As shown in Table 1, the dominant category is equity (with 591 products), followed by commodity (249) and credit (42).

Returns are reported in US dollars and measured in excess of the risk-free rate, typically LIBOR. The swap fee, if any, was also deducted from returns. So, the returns used in this study represent truly implementable risk premia strategies. The bank products are, indeed, investable because they are open to new clients and returns are reported net of transaction costs and fees. If anything, costs are probably slightly overstated here because there is usually room for negotiating fees with banks.

To avoid the backfill bias generated by backtests, HFR used returns after the live date only. Some series go as far back as 2006, but indexes are more generally available from 2010, which gives us about 11 years of data. Note that the period was particularly favorable to US equities and bonds, so performance in different environments is still an open question.

The indexes are constructed by first inversely weighting TRS returns by their historical volatility. Next, scaled returns are equally weighted across all products within each category. Finally, note that, like all hedge fund indexes, these BRP indexes track the performance of the entire group of covered products. This approach provides a useful benchmark for performance but ignores the potential benefits of product selection.

## Empirical Results

I first analyze the performance of hedge funds, conventional risk premia, and alternative risk premia. Then, I discuss how alternative risk premia can replicate hedge fund returns.

### Hedge Funds and Conventional Risk Premia.

We first examine the target market for hedge funds by using the HFR family of indexes, now widely used as standard benchmarks. These returns are net of all fees and are constructed live since 1994. The broad index (fund composite) is subdivided into four strategies: event driven, equity hedge, macro, and relative value. **Table 2** provides summary statistics for these five Hedge Fund Research Index (HFRI) series for the 2010–20 period.

During this period, as Table 2 shows, hedge funds experienced, in aggregate, an average arithmetic return of 4.7%, with a volatility of 6.2%, both annualized from monthly data. Subtracting the one-month US T-bill rate translates into an excess return of 4.2%. This return is not all alpha, however, because all HFRI are directional, as indicated by the high

**Table 2. Total Returns of Hedge Fund Indexes, 2010–20**

| Total Return Measure | HFR Fund Wgt. Composite Index | HFR Event-Driven Index | HFR Equity Hedge Index | HFR Macro Index | HFR Relative Value Index |
|---|---|---|---|---|---|
| Average | 4.7% | 5.2% | 5.8% | 1.9% | 4.8% |
| Standard deviation | 6.2% | 6.8% | 8.7% | 4.5% | 4.5% |
| Sharpe ratio | 0.67 | 0.69 | 0.61 | 0.30 | 0.97 |
| Skewness | –1.02 | –2.00 | –0.68 | 0.22 | –3.90 |
| Excess kurtosis | 5.69 | 13.69 | 3.36 | 0.22 | 29.01 |
| Auto(1) | 0.10 | 0.15 | 0.06 | –0.05 | 0.15 |
| Correlation, SPX | 0.89 | 0.82 | 0.91 | 0.41 | 0.74 |
| Correlation, Tr | –0.33 | –0.44 | –0.38 | 0.23 | –0.38 |
| Correlation, HY–Tr | 0.84 | 0.89 | 0.84 | 0.17 | 0.90 |

*Notes*: Average and standard deviation are annualized. Correlations reported are the first-order autocorrelation [i.e., Auto(1)] and correlations with SPX (S&P 500 Equity Index), Treasuries (Barclays–Bloomberg Treasury Index), and the HY–Tr spread (between the BB High-Yield Bond and Treasury Indices). Excess kurtosis is Pearson's kurtosis minus 3.

S&P correlations. Even so, the question of interest is whether alternative risk premia can replicate some of these hedge fund returns.

Next, **Table 3** reports for the 2010–20 period excess returns on three major market factors—the S&P 500, the Barclays–Bloomberg (BB) Treasury Bond Index, and the BB High-Yield Bond Index. These series are essentially buy-and-hold long-only indexes that can be implemented in practice at low cost.

Table 3 also shows the performance of the Fung–Hsieh trend-following factors for the same period. Fung and Hsieh (2004) developed the classic approach to hedge fund replication. Their seven-factor model includes the same three market factors plus a “small cap” size effect and three trend-following returns—on bond, currency, and commodity futures—later extended to short-term interest rates and equity indexes.[15] The returns on these five trend-following strategies do not include transaction costs and are essentially unfunded—that is, represent excess returns. As Table 3 shows, these trend factors are extremely volatile, reflecting their embedded leverage.[16] For comparison purposes, excess returns have been rescaled to a 10% volatility. Most trend factors did poorly over this period, calling into question their usefulness as sources of positive risk premia.

## Alternative Risk Premia.

**Table 4** describes the performance of the HFR bank risk premia indexes—19 indexes covering various asset classes and styles, with continuous data for the 2010–20 period.

Volatility numbers in Table 4 are generally high and widely different across series, which reflects the inverse volatility weighting process used in the construction of the indexes. As a result, I focus again on the average excess return for a 10% target volatility, as well as one-factor alphas.

Consider, first, the equity strategies’ performance in Panel A of Table 4. On the scaled measure, average returns are positive for the equity value and multi-style strategies. The scaled return for equity value is 6.9%, which is significant. Some of this return is attributable to directional SPX risk, but the remaining alpha is still positive.

Second, consider the rates category. The overall rates, carry rates, momentum rates, and volatility rates risk premia all have positive scaled returns, ranging from 3% to 6%. This performance is unlike the FH bond and STIR trend factors in Table 3, which are both negative. Note that the overall, carry, and momentum factors have high positive correlations with Treasury bonds. This result is as expected because rates carry strategies tend to invest in

**Table 3. Excess Returns of Market Factors and FH Trend Factors, 2010–20**

| Excess Return Measure | S&P 500 Equity Index | BB Treasury Index | BB High-Yield Index | Bond Trend Following | Currency Trend Following | Commod. Trend Following | STIR Trend Following | Equity Trend Following |
|---|---|---|---|---|---|---|---|---|
| Average | 13.6% | 2.9% | 7.0% | −9.7% | −24.9% | 4.5% | −108.7% | −44.3% |
| Standard deviation | 14.4% | 3.7% | 7.4% | 66.6% | 69.5% | 54.5% | 57.5% | 62.4% |
| Sharpe ratio | 0.95 | 0.76 | 0.95 | −0.15 | −0.36 | 0.08 | −1.89 | −0.71 |
| Exc. return, 10% vol | 9.5% | 7.6% | 9.5% | −1.5% | −3.6% | 0.8% | −18.9% | −7.1% |
| Skewness | −0.31 | 0.33 | −1.73 | 2.06 | 1.88 | 1.37 | 1.45 | 2.66 |
| Excess kurtosis | 1.62 | 0.46 | 11.32 | 6.86 | 5.50 | 3.39 | 3.53 | 10.03 |
| Auto(1) | −0.11 | 0.06 | −0.03 | 0.08 | 0.03 | 0.07 | 0.22 | 0.20 |
| Correlation, SPX | 1.00 | −0.32 | 0.78 | −0.49 | −0.34 | −0.30 | −0.31 | −0.40 |
| Correlation, Tr | −0.32 | 1.00 | −0.21 | 0.52 | 0.23 | 0.20 | 0.31 | 0.16 |
| Correlation, HY–Tr | 0.78 | −0.60 | 0.91 | −0.64 | −0.44 | −0.38 | −0.36 | −0.45 |

*Notes*: Returns for factors are measured in excess of the risk-free rate, taken as the one-month T-bill rate. The three major market factors are the SPX, Barclays–Bloomberg (BB) Treasury Index (Tr), and the BB High-Yield Index (HY). The five trend-following factors are from Fung-Hsieh (2004) and include bonds, currencies, commodities, short-term interest rates (STIR), and equities. For comparison, excess returns are also shown adjusted for 10% volatility. See also the notes to Table 2.

## Table 4. Performance of Bank Risk Premia, 2010–20

| BRP Excess Return Measure | Equity | Equity Carry | Equity Momentum | Equity Value | Equity Multistyle | Rates | Rates Carry | Rates Momentum | Rates Volatility |
|---|---|---|---|---|---|---|---|---|---|
| *A. Equity and rates indexes* | | | | | | | | | |
| Average | 0.5% | –0.4% | –0.8% | 5.1% | 4.8% | 4.4% | 4.8% | 9.5% | 6.0% |
| Standard deviation | 13.1% | 18.2% | 15.4% | 7.4% | 15.3% | 7.7% | 11.5% | 17.4% | 19.3% |
| Sharpe ratio | 0.04 | –0.02 | –0.05 | 0.69 | 0.31 | 0.58 | 0.42 | 0.55 | 0.31 |
| Exc. return, 10% vol | 0.4% | –0.2% | –0.5% | 6.9%* | 3.1% | 5.8% | 4.2% | 5.5% | 3.1% |
| Alpha, 10% vol | –10.8% | –4.8% | –3.8% | 3.5% | –5.4% | 5.6% | 5.6% | 6.3% | –1.0% |
| Skewness | –3.10 | –2.49 | –2.30 | –0.43 | –0.51 | –0.20 | –0.13 | 1.45 | –0.34 |
| Exc. kurtosis | 20.31 | 14.34 | 13.48 | 2.50 | 1.10 | –0.15 | 0.12 | 6.04 | 16.84 |
| Auto(1) | 0.14 | 0.01 | 0.13 | 0.14 | 0.01 | –0.04 | 0.04 | –0.02 | –0.03 |
| Correlation, SPX | 0.78 | 0.44 | 0.33 | 0.39 | 0.73 | 0.02 | –0.14 | –0.08 | 0.43 |
| Correlation, Tr | –0.31 | –0.27 | –0.07 | –0.14 | –0.16 | 0.46 | 0.53 | 0.36 | –0.18 |
| Correlation, HY–Tr | 0.75 | 0.53 | 0.35 | 0.25 | 0.54 | –0.05 | –0.22 | –0.20 | 0.52 |
| Memo: No. TRS | 591 | 36 | 73 | 157 | 49 | 97 | 37 | 27 | 23 |

| BRP Excess Return Measure | Credit | Credit Carry | Currency | Currency Carry | Currency Momentum | Currency Value | Commodity | Commodity Carry | Commodity Momentum | Multiasset |
|---|---|---|---|---|---|---|---|---|---|---|
| *B. Credit, currency, commodity, and multiasset indexes* | | | | | | | | | | |
| Average | 13.1% | 10.1% | –3.9% | –3.3% | 0.6% | 1.7% | 0.8% | 6.5% | –1.4% | 11.3% |
| Standard deviation | 29.0% | 30.1% | 11.8% | 20.7% | 22.2% | 13.0% | 11.8% | 14.5% | 18.3% | 19.0% |
| Sharpe ratio | 0.45 | 0.34 | –0.33 | –0.16 | 0.03 | 0.13 | 0.07 | 0.45 | –0.07 | 0.59 |
| Exc. return, 10%vol | 4.5% | 3.4% | –3.3% | –1.6% | 0.3% | 1.3% | 0.7% | 4.5% | –0.7% | 5.9%* |
| Alpha, 10%vol | –3.5% | –5.1% | –6.5% | –7.1% | 1.3% | 3.3% | –2.6% | 3.6% | 0.0% | –0.5% |
| Skewness | –0.97 | –3.17 | –0.63 | –0.20 | 0.30 | 0.18 | –0.66 | 0.92 | 0.49 | –0.47 |
| Exc. kurtosis | 14.74 | 25.01 | 1.98 | 0.39 | 2.47 | 4.72 | 3.36 | 5.29 | 1.88 | 1.20 |
| Auto(1) | 0.09 | 0.07 | 0.02 | –0.04 | –0.14 | 0.03 | 0.03 | –0.03 | –0.07 | –0.03 |
| Correlation, SPX | 0.74 | 0.73 | 0.31 | 0.49 | –0.11 | –0.20 | 0.34 | 0.10 | –0.08 | 0.68 |
| Correlation, Tr | –0.26 | –0.27 | –0.21 | –0.23 | 0.16 | 0.01 | 0.00 | 0.03 | 0.20 | 0.11 |
| Correlation, HY–Tr | 0.75 | 0.78 | 0.31 | 0.48 | –0.20 | –0.18 | 0.16 | –0.05 | –0.33 | 0.42 |
| Memo: No. TRS | 42 | 24 | 82 | 28 | 22 | 17 | 249 | 95 | 54 | 64 |

*Notes*: Performance is measured in monthly excess returns. Indexes were classified into asset classes (equity, rates, credit, currency, commodity, multiasset) and risk premia styles (carry, momentum, value, volatility, multistyle). The 19 reported indexes are those with continuous data for 2010–2020. See also the notes to Table 2. The alpha from a one-factor model on SPX adjusted to a 10% volatility is also shown. For reference, the last row in each panel reports the number of bank total return swaps (TRS) in each index as of 2018.

*Significant at the 5% level.

longer-term maturities as a result of generally positively sloped yield curves, and so they are long duration (see Martens, Beekhuizen, Duyvesteyn, and Zomerdijk 2019).

Third, consider the credit risk premia in Panel B of Table 4, where we only have the carry style for the entire period. These scaled returns are also positive, at around 4%. Credit carry tends to be long high-yield bonds to benefit from the higher carry, which is directional. This tendency is confirmed by the high correlation with the HY–Tr spread and, indirectly, with equities. Once adjusted for the SPX beta, alpha becomes negative.

Turning to the currency premia, Panel B of Table 4 shows that the overall index and carry have negative returns. This poor performance should help alleviate concerns about survivorship bias for these bank products. Currency carry tends to be long high-interest-rate currencies and short low-interest-rate currencies. Currency carry has a high correlation with SPX, 0.49. Indeed, Melvin and Shand (2017) documented that currency carry typically experiences drawdowns during financial crises. Taking SPX beta into account penalizes the return even further, for a large negative alpha.

Fifth, the commodity risk premia have experienced mixed returns. As shown in Panel B of Table 4, carry was positive with a scaled return of 4.5%. Finally, the multiasset risk premia have been positive, around 6%, and significant. Once again, much of this performance is attributable to the directional equity exposure.

Overall, these bank risk premia exhibit a range of returns, generally positive for equity, rates, and credit and mixed for currencies and commodities. A few average risk premia are positive and significant at the usual confidence levels, even with only 11 years of data. None of the negative premia is significant.[17]

Many of these bank risk premia have directional equity risk, however, which certainly helped their performance over this period, when equities were strongly up. The next question is the extent to which hedge fund returns can be replicated by bank risk premia.

## Hedge Fund Returns and Alternative Risk Premia.

To explore this question, I estimated traditional regressions of returns for hedge fund indexes on market factors and a sample of bank risk premia. First, returns on all long investments, starting with the hedge fund return, $R_t$, were adjusted to be in excess of the risk-free rate. This step allowed the intercept to be properly interpreted as alpha:

$$R_t = \alpha + \beta_M R_{M,t} + \beta_T R_{T,t} + \beta_H R_{H,t} + \left[\sum_{j=1}^{K} \beta_j R_{j,t}\right] + e_t, \qquad (1)$$

where the subscripts $M$ and $T$ represent the excess return on, respectively, the S&P 500 and the Treasury bond index and subscript $H$ represents the return on a long–short position in the high-yield/Treasury bond indexes. The term in brackets represents the contribution of ARP products.

To be meaningful, this linear factor model must include actual returns on investable strategies as factors. This setup also illustrates the importance of transaction costs. Consider, for example, a purely passive hedge fund that perfectly replicates the traditional US equity momentum factor. The typical empirical research would use the Fama and French (1993) ARP factor, which should be the only significant variable, with a slope of 1.0. This strategy, however, entails substantial turnover, with a cost estimated by Novy-Marx and Velikov (2016) at 8% out of a 16% gross return. The regression would then show a negative alpha, –8%, leading to the wrong conclusion that the fund was underperforming. This result can be avoided by using, instead, the HFR bank product for equity momentum.

Because bank risk premia are designed to mimic some of the strategies used by hedge funds, one would expect a reasonably good fit for some fund types. HFR reports a large number of risk premia, however, reflecting the breadth of hedge fund strategies. To ensure parsimony, one approach is to prespecify a small set that is most appropriate for the hedge fund strategy.

The test started with the composite hedge fund index together with its four strategies, which were regressed on five broad ARP. The “Avg. ER” column in **Table 5** reports the average excess return on the hedge fund index; the next columns describe regression estimates for Equation 1.

First, note the very high $R^2$s. They range from 48% for the macro index to 90% for the equity hedge index. In addition, note significant exposures to the three major market factors.[18] Because these factors are strongly correlated, the interpretation of the slope coefficients is subject to the usual caution. Nevertheless, the $R^2$ and the alpha are not invalidated.

Table 5 also shows that many exposures to bank risk premia are substantial. The partial $R^2$s, defined as the fraction of the variance remaining after the

## Table 5. Explaining Broad Hedge Fund Categories with General Bank Risk Premia, 2010–20

| | | Three Market Factors + Five BRP Factors | | | | | | | | | | 5 BRP + 3 M | 5 FH + 3 M | 5 BRP + 3 M and 5 FH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hedge Fund Index | Avg. ER | Alpha | Equity | Treasury | HY–Tr | BRP Equity | BRP Rates | BRP Credit | BRP Currency | BRP Commodity | $R^2$ | $R^2$, Partial | $R^2$, Partial | $R^2$, Partial |
| Composite (fund weighted) | 4.30% | 0.05% | 0.16 | 0.32 | 0.26 | 0.08 | −0.08 | 0.03 | 0.03 | 0.06 | 90.2% | 25.9% | 3.6% | 35.2% |
| | | 0.07 | 6.58 | 4.23 | 5.47 | 3.30 | −2.69 | 3.11 | 1.64 | 3.68 | | (0.0000) | (0.4644) | (0.0000) |
| Event driven (ED) | 4.91% | 1.62% | 0.05 | 0.25 | 0.46 | 0.10 | −0.10 | 0.03 | 0.01 | 0.01 | 86.7% | 16.2% | 4.5% | 24.8% |
| | | 1.78 | 1.50 | 2.58 | 7.68 | 3.28 | −2.62 | 2.61 | 0.52 | 0.71 | | (0.0005) | (0.3220) | (0.0000) |
| Equity hedge (EH) | 5.50% | −0.52% | 0.29 | 0.30 | 0.33 | 0.06 | −0.14 | 0.03 | 0.04 | 0.07 | 91.3% | 22.4% | 2.9% | 39.2% |
| | | −0.56 | 9.19 | 3.08 | 5.40 | 1.90 | −3.62 | 2.25 | 1.87 | 3.50 | | (0.0000) | (0.6030) | (0.0000) |
| Macro (MA) | 1.19% | −1.16% | 0.10 | 0.38 | −0.16 | 0.08 | 0.02 | 0.03 | 0.04 | 0.14 | 47.6% | 24.7% | 18.2% | 39.2% |
| | | −0.97 | 2.39 | 3.04 | −2.05 | 2.03 | 0.37 | 1.74 | 1.58 | 5.10 | | (0.0000) | (0.0001) | (0.0000) |
| Relative value (RV) | 4.50% | 2.25% | −0.04 | 0.33 | 0.41 | 0.11 | −0.03 | 0.02 | 0.00 | −0.02 | 87.8% | 25.4% | 16.5% | 13.8% |
| | | 3.93 | −1.91 | 5.43 | 10.84 | 5.37 | −1.36 | 2.02 | 0.05 | −1.88 | | (0.0000) | (0.0004) | (0.0000) |

*Notes*: HFR hedge fund returns, including the composite index and the four major strategies, were measured in monthly excess returns over the period. The "Avg. ER" column reports the annualized average excess return. The next columns show regressions on three major market factors (excess return on the S&P 500, on the BB Treasury Index, and on a long–short BB High-Yield vs. Treasury index) and the five general bank products (BRPs). Rows below the regression statistics report *t*-statistics. The "5 BRP + 3 M" column reports the partial $R^2$ from adding the five BRP to the three market factors (M). The *p*-values for the joint *F*-tests are in parentheses. The "5 FH + 3 M" column reports the partial $R^2$ from adding the five Fung–Hsieh (FH) factors to the three market factors. The last column reports the partial $R^2$ from adding the five BRP factors to the set of three market factors plus the five FH factors.

three-factor model that is explained by adding the five BRP factors, are around 25%. This implies a correlation of about 50% between hedge funds and ARP, which is a rough measure of the replication ratio described previously. In all cases, the *F*-statistic for the joint five BRP factors is highly significant.[19] Also, the partial $R^2$s from the five FH trend factors are systematically lower than those in the previous column, which demonstrates the improved explanatory power of these BRP factors.

In addition, Table 5 shows that once these market factors and ARP are taken into account, not much alpha is left. Alpha is systematically lower than the starting average excess return.

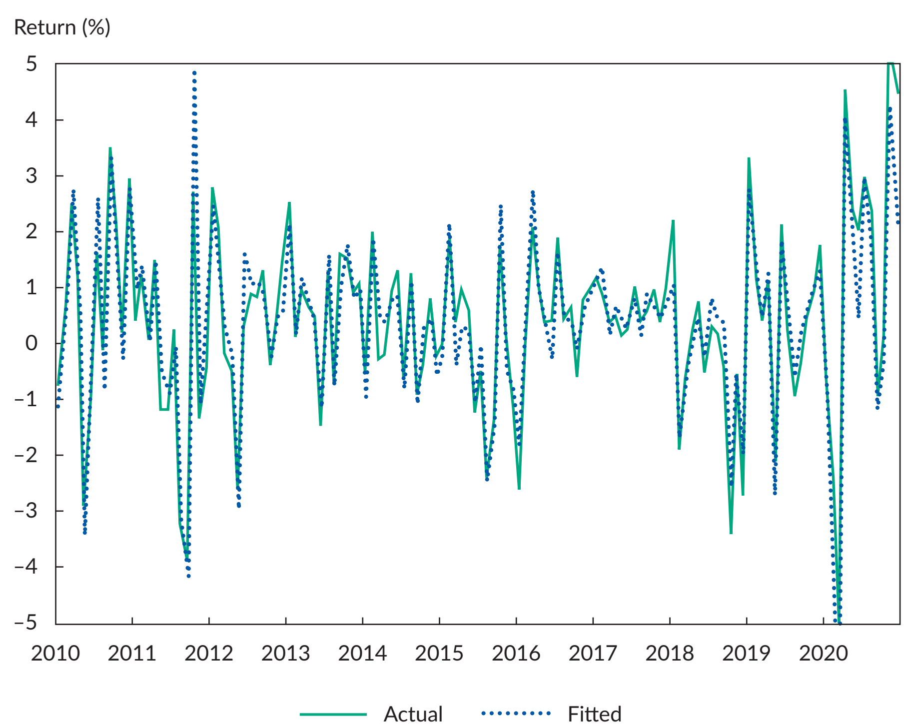
The usefulness of this approach can also be visualized by plotting the monthly returns on the HFR Composite Index together with the fitted value from this eight-factor model. **Figure 2** shows that the quality of the fit is extremely good.

So far, the analysis has considered the general sample of hedge funds and has included both judgmental and quantitative approaches. Quantitative hedge fund strategies, however, are more likely to use rules-based approaches, such as alternative risk premia. I selected the HFR Quantitative Directional Index (within the equity hedge space), the Macro Currency Index, the Macro Commodity Index, and the Macro Systematic Index.

In this analysis, I could use a more targeted approach and, from prior knowledge of the industry, pick *a priori* the BRP indexes that are most likely to explain each hedge fund category. For instance, for the Macro Currency funds, I chose the three foreign exchange (FX) premia—namely, carry, momentum, and value. Similarly, for the Macro Commodity funds, I chose the two available commodity premia. For the Quantitative Directional Equity funds, I chose the four equity ARP. For the Macro Systematic funds, which typically use trend-following rules, I chose the five momentum ARP. **Table 6** shows the results.

Many of the risk premia slope coefficients shown in Table 6 are positive and significant, as expected. In all cases, the *F*-statistic for joint significance of the selected BRP factors is highly significant. The Macro Currency Index loads heavily, and positively, on the FX carry and FX momentum risk premia. The Macro Commodity Index loads heavily on the two commodity risk premia. The Quantitative Directional Index has a high equity beta, as expected from its name,

**Figure 2.** Comparison of Returns for the HFR Composite Index and Fitted Eight-Factor Model




*Notes*: The monthly returns of the HFR Composite Index are compared with the fitted value of the eight-factor model that includes three market risk factors plus the five general BRP indexes (equities, rates, credit, currency, and commodities).

**Table 6. Explaining Specific Hedge Fund Categories with Specific Bank Risk Premia, 2010–20**

| | | | 3 Market + BRP Factors | | | | | | | | | | 3 M + 5 FH Factors |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Market | | | Specific Bank Risk Premia | | | | | | | |
| Hedge Fund Index | Avg. ER | Alpha | Equity | Treasury | HY–Tr | Equity Carry | Equity Momentum | Equity Value | Equity Multistyle | | *F*-Test | $R^2$ | $R^2$ |
| Equity Quantitative Directional | 5.03% | −0.52% | 0.39 | −0.06 | −0.02 | 0.02 | 0.02 | 0.02 | 0.07 | | 4.1 | 84.8% | 84.0% |
| | | −0.51 | 10.22 | −0.64 | −0.40 | 1.16 | 0.97 | 0.54 | 2.58 | | (0.0040) | | |
| | | Alpha | Equity | Treasury | HY–Tr | FX Carry | FX Momentum | FX Value | | | | | |
| Macro Currency | 0.52% | 0.67% | −0.02 | 0.13 | −0.04 | 0.06 | 0.04 | 0.03 | | | 12.7 | 26.7% | 17.4% |
| | | 0.70 | −0.69 | 1.58 | −0.82 | 4.52 | 3.82 | 1.52 | | | (0.0000) | | |
| | | Alpha | Equity | Treasury | HY–Tr | Commodity Carry | Commodity Momentum | | | | | | |
| Macro Commodity | 0.82% | −2.23% | 0.06 | 0.31 | 0.22 | 0.08 | 0.09 | | | | 25.6 | 43.6% | 26.9% |
| | | −1.88 | 1.41 | 2.88 | 2.89 | 3.57 | 4.51 | | | | (0.0000) | | |
| | | Alpha | Equity | Treasury | HY–Tr | Equity Momentum | Rates Momentum | FX Momentum | Commodity Momentum | Multi Momentum | | | |
| Macro Systematic | 0.97% | −2.36% | −0.05 | 0.35 | 0.01 | 0.01 | 0.01 | 0.12 | 0.09 | 0.23 | 41.1 | 71.5% | 37.5% |
| | | −1.70 | −0.11 | 2.60 | 1.68 | 0.36 | 0.57 | 6.70 | 4.01 | 7.20 | (0.0000) | | |

*Notes*: Regressions use HFR hedge fund returns for a sample of specific quantitative substrategies, measured in monthly excess returns over the period. The "Avg. ER" column reports the annualized average excess return. The next columns show regressions on the three major market factors (excess return on the S&P 500, on the BB Treasury, and on a long–short BB High-Yield vs. Treasury) plus a sample of bank risk premia prespecified for a specific hedge fund strategy. Rows below the regression statistics report *t*-statistics. The *F*-statistic tests for zero coefficients on the BRP factors, with *p*-values given in parentheses, all below 1%. The last column reports the $R^2$ from the three major market factors plus the five FH trend factors.

but also loads on the equity multistyle risk premia. Finally, the Macro Systematic Index has low directional exposure to equities, rates, and credit, but it loads heavily, and positively, on three momentum risk premia. In that case, the total $R^2$ is 72%—substantially higher than for the FH model, which is shown in the last column.

As in Table 5, not much alpha is left when taking into account the market risk factors and strategy-specific ARP. These results are in line with Bhardwaj, Gorton, and Rouwenhorst (2014), who ran regressions of Commodity Trading Advisor index returns on several risk premia factors over the 1994–2012 period. They found the most significant factors to be commodity and FX momentum. The authors reported insignificant alphas, even though their factors did not include transaction costs.

Instead of *a priori* specification, another approach is to systematically search over the risk premia that provide the best fit to hedge fund returns for the entire sample of 22 HFR substrategies. This stepwise approach is demonstrated in **Table 7**. The first step is to regress each substrategy return against the three major market factors to generate "residuals." These residuals are then correlated with each of the 13 BRP factors individually; only those with univariate significance are selected for inclusion in a multivariate regression.

Table 7 is generally consistent with the prespecified approach in Table 6. Currency and commodity funds load most heavily on currency and commodity risk premia. The macro systematic funds load on momentum factors. Table 7 also reveals, however, which factors seem to matter for other strategies. For instance, merger arbitrage funds load positively on the rates volatility factor, which is short volatility. Indeed, merger arbitrage spreads tend to widen when implied volatility spikes. Table 7 also shows that many strategies are not explained well by systematic risk premia. This category includes most equity strategies (other than quantitative) and others that are highly security specific, such as activist and distressed debt funds. Overall, the analysis presented here can be used as a framework for discovering the portion of hedge fund returns that can be replicated by ready-made systematic strategies.

## Conclusions

Alternative risk premia products are the next logical step in the progression toward automation of active management. Indeed, such trading algorithms aim to capture compensated risk factors, or risk premia, that may be embedded in returns provided by hedge funds. The development of this new market, now estimated at around $360 billion, is a response to investors' search for lower fees.

This article has summarized the performance of the ARP market as provided by banks' total return swaps. In this approach, investors outsource both the execution and design of the trading strategies to broker/dealers. Unlike conventional academic risk premia, however, these products are fully investable because they account for all transaction costs. As a result, these bank products provide realistic estimates of returns on risk premia strategies.

Using indexes provided by HFR for the 2010–20 period, this article reports several new results. Even over this short period, I found that several risk premia provide significantly positive returns, especially within equities, rates, and credit. Currency products, in contrast, have not performed well. The performance of commodity products has been mixed. Admittedly, much like hedge funds, many of these bank products have directional exposure to equities.

Armed with the information about the performance of these products, I turned to the question of whether hedge fund performance can be replicated by traditional market factors (equities, rates, and credit) augmented by bank risk premia. I found a significant increase in explanatory power from the BRP products. Interestingly, this model dominates the traditional workhorse of hedge fund replication, the famous Fung–Hsieh (2004) seven-factor model. So, this new framework can provide improved replication of hedge fund index returns. This improvement is especially the case for quantitative hedge funds, which are more likely to follow systematic trading rules than other funds, but less the case for security-focused hedge funds. Finally, I found that any excess return provided by these hedge fund indexes is largely eaten away after accounting for market factors and a selection of bank risk premia.

These results should help inform investments in alternative risk premia and hedge funds. In particular, the BRP products can help guide the manager search process by splitting the track record into contributions from ARP exposures and alphas. A high $R^2$ with low alpha implies that investors should allocate to ARP. In contrast, a low $R^2$ and high alpha is an indication of manager skill.

## Table 7. Explaining General Hedge Fund Categories with General Bank Risk Premia, 2010–20

| | Average | | Slopes on BRP | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Strategy | Excess Return | 3-Factor Residual | EQ Carry | EQ Mom. | EQ Value | EQ Multi | CO Carry | CO Mom. | CR Carry | CU Carry | CU Mom. | CU Value | RT Vol | RT Carry | RT Mom. |
| EHQuant Direct. | 5.0% | –1.2% | | | | | | | | | | | | | |
| EHEq. Mkt. Neutr. | 1.8% | 0.0% | | 0.022* | | 0.033* | | | | | | | | | |
| EHFund Gro. | 5.1% | –3.1% | | | | | 0.075* | | | | | | | | |
| EHFund Val. | 6.4% | –1.2% | | | | | | | | | | | | | |
| EHMulti | 6.0% | –1.4% | | | | | | | | | | | | | |
| EDMerger Arb. | 3.3% | 0.6% | 0.013 | 0.032 | | | | | | | | | 0.041* | | |
| EDCredit Arb. | 5.7% | 2.5% | 0.053* | 0.038* | | | | | | | | | | | |
| ED-Distressed | 4.7% | 1.4% | | | | | | | | | | | | | |
| EDSpecial Sit. | 5.5% | 0.0% | 0.045* | 0.029 | | | | | | | | | | | |
| EDActivist | 6.7% | –1.8% | | | | | | | | | | | | | |
| EDMulti | 3.5% | –0.3% | | | | | 0.059* | | | | | | | | |
| MACommodity | 0.8% | –2.2% | | | | | 0.028 | 0.038* | | 0.044* | 0.074* | | | | |
| MACurrency | 0.5% | 0.1% | | | | | 0.042* | | | 0.049* | 0.029 | | | | |
| MASystematic | 1.0% | –4.7% | | | | | | 0.027 | | | 0.127* | | | | 0.087* |
| MADiscretion. | 1.1% | –1.5% | | | | | 0.034* | | | | 0.053* | | | | |
| MATrading | 2.5% | –0.3% | | | | | | 0.043* | | | | | | | |
| MAMulti | 2.2% | –2.2% | | 0.044* | | | | 0.056* | | | 0.037* | | | | |
| RVConvert. Arb. | 4.9% | 1.8% | | | | | | | | | | | | | |
| RVCorporate | 5.0% | 1.2% | 0.032* | 0.016 | | | | | | | | | | | |
| RVSovereign | 3.2% | 0.0% | | 0.052* | | | | | | | | | | | |
| RVABS | 6.3% | 4.8% | 0.009 | 0.075* | | | | | | | | | 0.031 | | |
| RVMulti | 4.1% | 1.6% | 0.020 | 0.020* | | | | | | | | | | | |

*Notes*: EQ = equity; CO = commodities; CR = credit; CU = currency; RT = rates; Mom. = momentum; EH = equity hedge; ED = event driven; MA = macro; RV = relative value. Regressions use HFR hedge fund returns for substrategies available with monthly excess returns over the period. The "Average" columns report the annualized average excess returns and the alpha from the three major market factor model. The residuals of this model were regressed against 13 BRP individually; products were selected on the basis of univariate significance. Shown are the multivariate slopes of the residuals on the selected ARPs.

*Significant at the 5% level.

## Editor's Note

Submitted 12 January 2021

Accepted 22 July 2021 by William N. Goetzmann

## Notes

1. As with hedge funds, this number is somewhat arbitrary. For bank products, the size refers to the TRS notional amounts. The trading strategies, however, are both long and short and can have varying levels of leverage and volatility for the same notional.

2. A notable exception is Suhonen, Lennkh, and Perez (2017), who examined backtest overfitting in ARP strategies. To our knowledge, this is the only published paper on such bank products.

3. Harvey and Liu (2020) documented some 400 equity factors published in top journals and argued that many must be false.

4. Recent academic research has started to examine the impact of trading costs for US equities. The difficulty lies with the estimation of spreads, even without considering market impact. Novy-Marx and Velikov (2016) analyzed US equity strategies and found that the momentum strategy, for example, incurs transaction costs of about 8% per year, which eats into half of the gross returns. Strategies with even higher turnover do not survive the inclusion of transaction costs.

5. Cremers, Petajisto, and Zitzewitz (2012) showed that standard benchmarks, such as the S&P 500 Index, have nonzero and significant alphas when the traditional CRSP/Fama–French factors are used. Because such benchmarks should have no alpha, the authors proposed using, instead, factor models based on tradable indexes. Berk and Van Binsbergen (2015) also argued that using academic factors that ignore transaction costs tends to bias mutual fund alphas downward. More recently, Barras, Gagliardini, and Scaillet (forthcoming) examined skills in the mutual fund industry by using tradable indexes. Black (2012) extended the Fung–Hsieh model to other variables, but many of them are not directly tradable, such as the Chicago Board Options Exchange VIX.

6. Ideally, expected risk premia should be estimated over very long periods. For instance, risk premia with Sharpe ratios of 0.40 require 25 years of returns to reach a $t$-statistic above 2 so the investor can be confident that the expected return is positive. The 2010–20 period is the longest, however, for which the data are available for a broad sample of products.

7. According to eVestment (2019). In addition, some managers charge additional expenses, such as research and data costs—even "team costs" to the fund.

8. Indeed, Ben-David, Birru, and Rossi (2020) suggested that the effective incentive fee is, in reality, 2.5 times the average contractual rate (e.g., around 50% instead of 20%).

9. The ability to offer such UCITS funds is a result of regulations for mutual funds in Europe giving some flexibility for using derivatives and leverage, which are essential for expanding the traditional long-only investment universe. Such UCITS offerings became feasible because UCITS IV, adopted in 2009, requires limits on notional amounts or on value at risk (VaR). In the United States, the SEC has adopted new rules that significantly expand the use of derivatives for registered investment companies, requiring the implementation of risk management programs, including VaR limits (see SEC 2020).

10. *Principles for Financial Benchmarks* (IOSCO 2013) sets out best practices for creating financial benchmarks. They include content and transparency of the methodologies and governance processes. For example, the prices used to determine the index should ideally come from outside the bank to avoid situations where traders at that bank have an incentive to manipulate the value of the index.

11. "Carry" risk premia tend to buy higher-yielding assets (and, conversely, to sell lower-yielding assets). "Value" tends to buy assets that are relatively cheap when comparing prices with some fundamental value. "Momentum" or "trend" strategies tend to buy assets that have gone up in price recently. Finally, the "volatility" ARP strategy typically sells implied volatility, which tends to be higher than future realized volatility. Other categories are also used, especially within the equity space—such as size, quality, and low beta/volatility.

12. For instance, Harvey, Liu, and Zhu (2016) analyzed 315 published factors and the effects of data mining and multiple testing. Harvey and Liu (2015) discussed the common practice of applying a 50% haircut to the Sharpe ratios.

13. The reduction in alpha can be ascribed to two effects—data mining and/or crowding. McLean and Pontiff (2016) reviewed the postpublication performance of 97 variables that academic research had shown to predict stock returns. They found that returns are 26% lower out of sample and 58% lower postpublication, indicating both a data-mining effect (evidenced by the lower out-of-sample performance) and a crowding effect (because of investors learning about a mispricing).

14. In practice, banks have totally automated processes that price these products on a daily basis and post the information on, for instance, Bloomberg. This practice is unlike that of most hedge funds, where the net asset value is usually struck once a month only and then uploaded onto hedge fund databases, typically by an analyst. So, there is more room to delay or stop reporting returns for hedge funds than for bank products.

15. As detailed in Fung and Hsieh (2001), these returns are constructed from returns on "lookback straddles," which are replicated in practice by dynamically rolling long option positions. For each asset class, the return is an equally weighted average of four to six global markets. The data are available at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/.

16. The strategies purchase options, which have embedded leverage. For STIR, the annualized average return is –109%, which reflects the high volatility of 57%. Using arithmetic averages ensures consistency between total returns, excess returns, and alphas but sometimes leads to unusual values when annualized. If the compound return had been used instead, this strategy would have returned –71% per year, or a loss of most of its capital, in this period.

17. With this data-set size, a Sharpe ratio in excess of 0.59 is required to translate into significance at the 5% level.

18. Illiquidity in hedge fund investments could lead to an understatement of exposures. Getmansky, Lo, and Makarov (2004) discussed an adjustment based on lagged index values, which typically increases beta and lowers alpha further for hedge funds. Illiquidity also shows up in positive Auto(1) coefficients, however, as reported in Table 2 and Table 3. [The Auto(1) coefficient is the slope coefficient from a time-series regression of a variable on its preceding value.] Bank products offer daily liquidity, invest in liquid instruments, and indeed display low Auto(1) coefficients. The five hedge fund series do show higher autocorrelations, reaching 0.15, which is still not significant, however, suggesting that liquidity has improved over time.

19. Some of the BRP slopes are negative and significant. The reason could be collinearity between the variables. In practice, because these indexes cannot be shorted, the analysis could be repeated by setting the negative coefficients to zero. This adjustment is similar to Sharpe's (1992) return-based style analysis, which regresses returns to mutual funds on asset class returns, forcing the slope coefficients to be positive because mutual funds cannot go short.

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