Factor Analysis

Factor analysis can be a powerful tool for portfolio construction, capital allocation and attribution—helping investors to identify key risks and assess manager "alpha" generation.

Dan Golosovker, Mark Salzman, John Verberkmoes

1. Introduction

A critical aspect of investing is understanding the underlying drivers of risk and return. Factor models provide an analytical lens to assess what risks are contained within a portfolio or an asset. We can do this by statistically decomposing a return stream into constituent factors, a measure of an asset's systematic sources of risk. At the portfolio level, factor modeling can transform a portfolio with hundreds of assets and securities into a more legible portfolio of several factors (and a residual). This can provide insight into which risks are actually contributing to portfolio returns, and what could be done to create a more balanced portfolio.

In this piece, we first generally describe how factor models work. Then, we dive deeper with the help of three case studies that illustrate how factor analysis can be applied to assess portfolio and individual assets:

1. Portfolio macro risk factors—What are the risks a typical investor is exposed to?
2. Equity risk factors—How are investors exposed to common equity return factors?
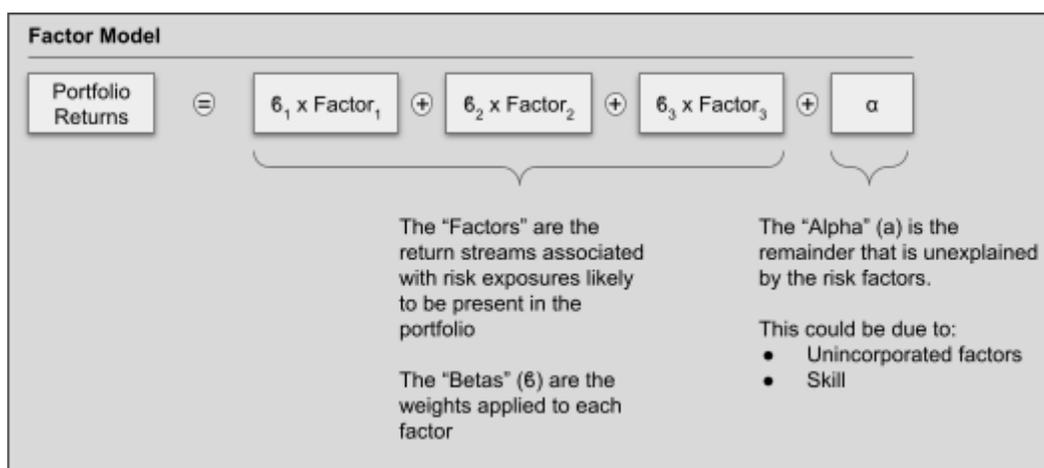3. Alternatives—Is there beta in the alpha?

We've chosen these case studies both to provide an introduction to the concepts behind factor models and to illustrate some practical use cases.

2. Key concepts and background

Factor models are based on time-series regressions of portfolio or asset returns (the independent variable) to a set of time series (the dependent variables or "factors"). Essentially, we want to decompose returns into a set of building blocks we call "factors," which represent the precise

concept we're interested in. These selected factors are often simply the returns of common market risk factors (e.g., the S&P 500 or the U.S. 10-Year Treasury Bond) or strategies (e.g., value or momentum style factors). Different building blocks receive different weights in the model (i.e., "betas"), depending on their importance in recreating the return stream under investigation. These weights can be positive or negative.

Whatever isn't explained by the weighted combination of factors is considered "alpha". Alpha can be the result of missing factors that aren't considered in the model. One of those missing factors could be investor "skill," which is uncorrelated with common market factors. If skill-based alpha exists, it's valuable because it is unrelated to the common market risk factors and thus can provide additional portfolio returns while not substantially increasing the overall risk level of the portfolio.

Factor Model

$$\text{Portfolio Returns} = \beta_1 \times Factor_1 + \beta_2 \times Factor_2 + \beta_3 \times Factor_3 + \alpha$$

The "Factors" are the return streams associated with risk exposures likely to be present in the portfolio

The "Betas" (β) are the weights applied to each factor

The "Alpha" (a) is the remainder that is unexplained by the risk factors.

This could be due to:
- Unincorporated factors
- Skill

High-level steps in running a factor regression include:
1. Select the portfolio or asset to analyze—Gather return data for the portfolio or asset to be analyzed. Careful consideration should be given to the time period chosen.
2. Factor selection—Determine the factors to be used and the time series (in this case, typically a return series). Factors are usually selected based on a set of criteria including:
   a. Actionable—Risk factors are ideally investable
   b. Orthogonal—Factors should be generally uncorrelated
   c. Applicable—Factors should represent exposures likely to be embedded in the portfolio or asset under examination
3. Factor processing—In some cases, you will want to transform the raw factors to enhance one of the above criteria. This could include mathematically ensuring that factors are orthogonal by residualizing one factor to another, for instance.

4. Run regression—Select the regression method suitable for your intended purpose. For example, you may want a method that includes variable selection (i.e., includes or excludes factors based on statistical measures, such as LASSO).

5. Review factor statistics—Assess the significance of factors and plot the residuals to check for consistency with regression assumptions.

6. Interpret your analysis—What are the key takeaways from the analysis? What can you conclude—or *not* conclude—from the results? (For instance, is the alpha from skill or missing factors?) What underlying factors may be missing (e.g., style factors, return from embedded foreign exchange)? What characteristics of the inputs might lead to misleading results? For example,is the timeframe long enough? Are true returns accurately captured?

3. Application #1: portfolio macro risks

As a first application of factor analysis, we take a top-down look at portfolios' factor exposures. This can be helpful in understanding both what factors are present and to what degree each factor is driving performance. To the extent a model is unable to explain performance, this can also be helpful in raising the question of what additional, unaccounted factors may be present in the portfolio.

For the initial step, we select a set of factors for our analysis. The factors in this case should adhere to our criteria of (1) actionable, (2) orthogonal and (3) applicable. In terms of #3, because this is portfolio-wide analysis, we should select factors that represent broad drivers of asset-class performance. So, considerations such as economic growth, inflation and overall risk premiums should be front and center.

| Macro Factors	Description	Intent
SP500_RET	The return of the equity market—risk-free rate	Captures exposure to economic growth and profitability of companies
BEI_CHG	Market-based measure of expected inflation. Break-even inflation is measured by the difference in yield between a nominal bond and an inflation-linked bond of similar maturities.	Captures exposure to changes in market-priced inflation rates
VIX_CHG	Market index representing the	Captures exposure to the changes in

	expectations for equity volatility over the coming 30 days	equity market volatility
REAL_CHG	Real interest rates of inflation-linked bonds	Captures exposure to the real future interest rate risk (time value of money)

To illustrate the power of macro factors, we've decomposed factor exposure of the aggregate returns of all assets modeled on the Addepar platform. As shown in the table and chart below, the macro factors explain all but 50 bps of returns on a monthly basis. The thousands of securities held by investors, by and large, can be explained by a small set of macro risk factors. This tool greatly reduces the complexity of understanding portfolio risk exposure and can serve as an input in constructing a truly diversified asset allocation.

Factor Replication of Returns of Aggregated Assets on the Addepar Platform
%, Cumulative Return (2016–2022)
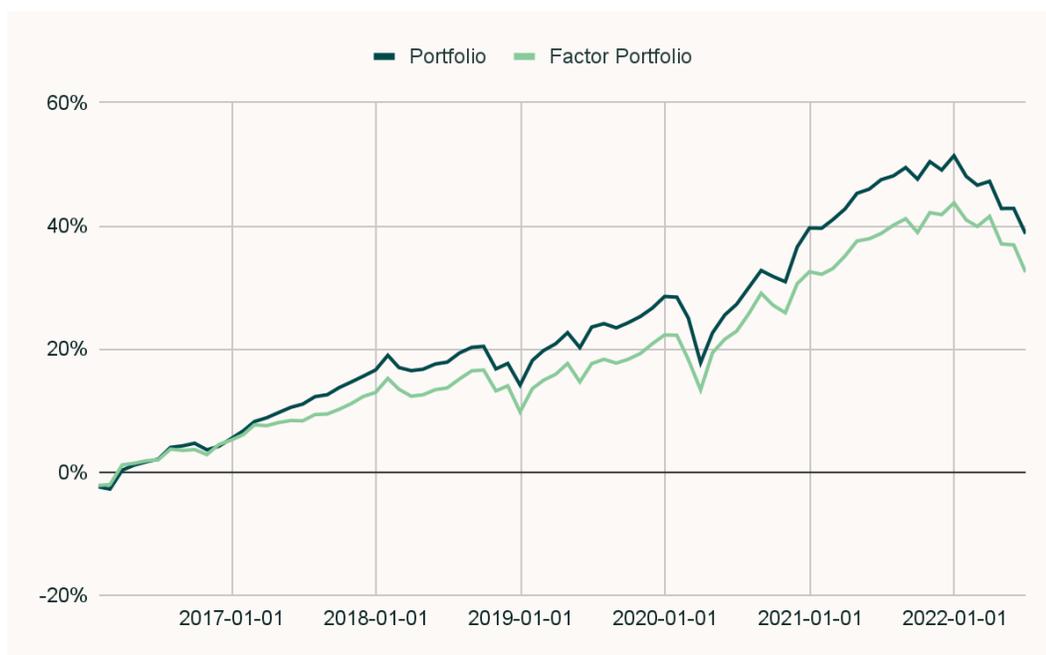
	SP500_RET	VIX_CHG	BEI_CHG	REAL_CHG	Constant
Factor	0.44	0.00	0.01	-0.01	0.06%

4. Application #2: equities risks

Next, we apply factor analysis to a single asset class: equities. Factor analysis can be useful to drill into sub-portfolios (e.g., equity, credit or alternatives) using factors tailored to the particular asset class under examination. A classic equity factor framework, which we will use here, is the Fama-French factors, which were first proposed in their landmark 1992 paper.[1]

Fama French Factors	Name	Description	Intent
Market Excess Return	Market Return	The return of the equity market—risk-free rate	Capture return of broad stock market
SMB	*Small Minus Big*	Basket of small market capitalization stocks minus basket of large capitalization stocks	Capture difference in return seen between small and large cap equities
HML	High Minus Low	Basket of of high book-to-value stocks minus basket of low book-to-value stocks	Capture difference in return between equities representing "cheap vs. expensive" value

To illustrate the power of factor decomposition, we've produced factor exposure estimates for three portfolios of liquid ETFs that have a high loading of one of these Fama-French factors. The table below shows the factor loadings followed by cumulative returns of the ETFs relative to a portfolio generated from the factor loadings.

One may observe that the replications tend to be visibly quite strong, although some drift occurs during the stressed markets at the onset of the COVID-19 pandemic. Considerations that may be driving the differences include the fact that Fama-French factors are calculated off of a relatively broad set of firms listed on AMEX, NYSE and the NASDAQ, while ETFs tend to be based on more narrowly defined indices. Additionally, steps are taken to ensure the SMB factor is independent of HML, which SPY–IWM would not take into account.
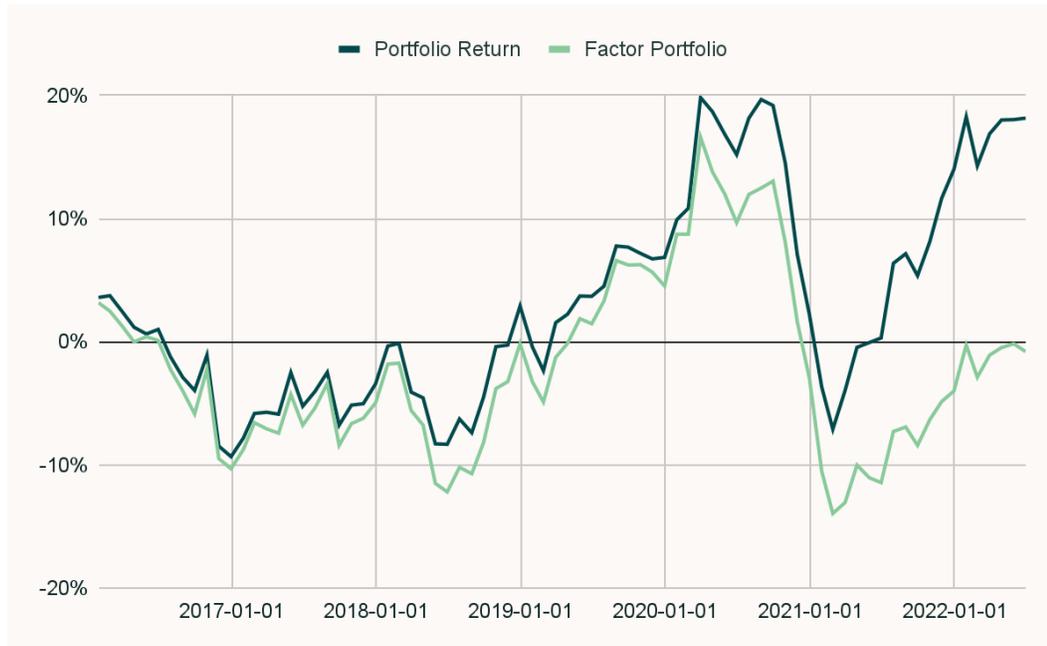
	MKT_EX	SMB	HML	Constant
SPY	0.97	-0.16	0.01	0.10%
SPY–IWM	-0.04	-0.98	-0.18	0.25%
SPYV–SPYG	-0.13	0.13	0.58	-0.16%

[1] Fama, E. F.; French, K. R. (1992). "The Cross-Section of Expected Stock Returns". *The Journal of Finance*. 47 (2): 427.
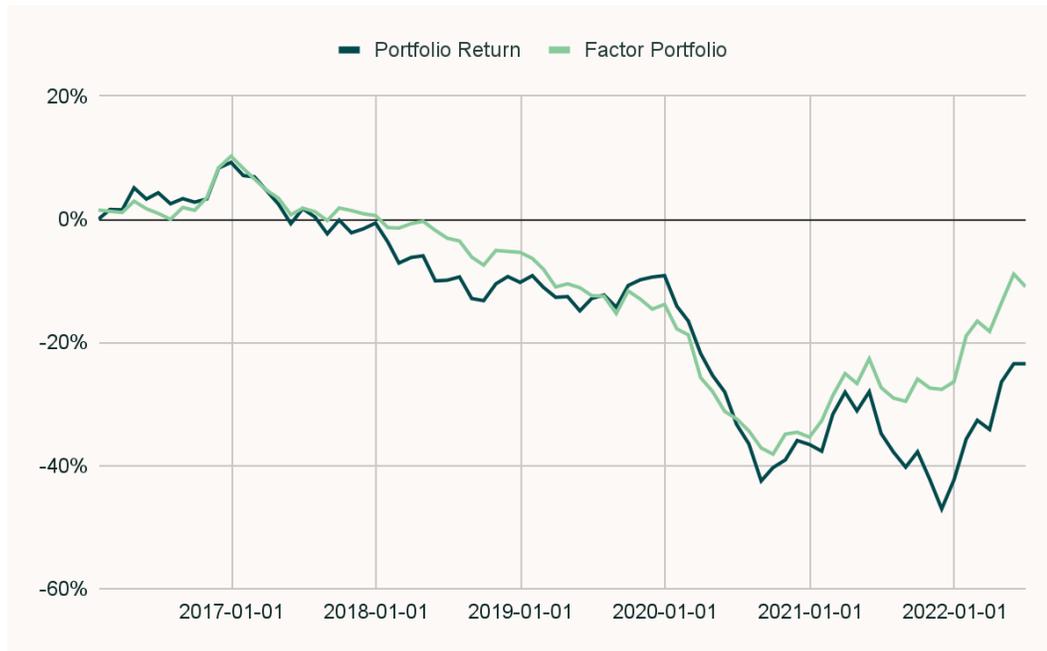
Factor Replication of S&P 500

%, Cumulative Return (2016–2022)
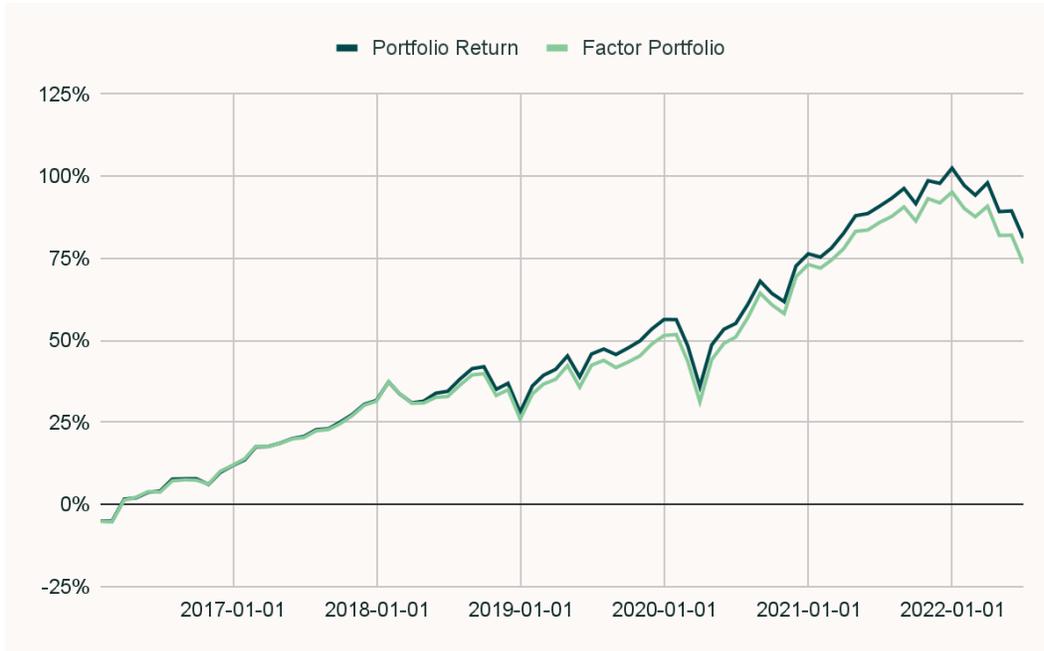
Factor Replication of S&P 500–Russell 2000

%, Cumulative Return (2016–2022)

Factor Replication of S&P 500 Value Portfolio–S&P 500 Growth Portfolio
*%, Cumulative Return (2016–2022)*

Applying this to the aggregate equity assets of investors, we see an almost perfect fit using our factor decomposition. Across all clients, the style factors largely wash out and we're left with more or less just the market factor. On an individual portfolio basis, however, there's much more variation in factor loadings.

	MKT_EX	SMB	HML	Constant
Factor	0.86	0.00	0.03	-0.08%

Factor Replication of Aggregate Addepar Equity Portfolio

%, Cumulative Return (2016–2022)
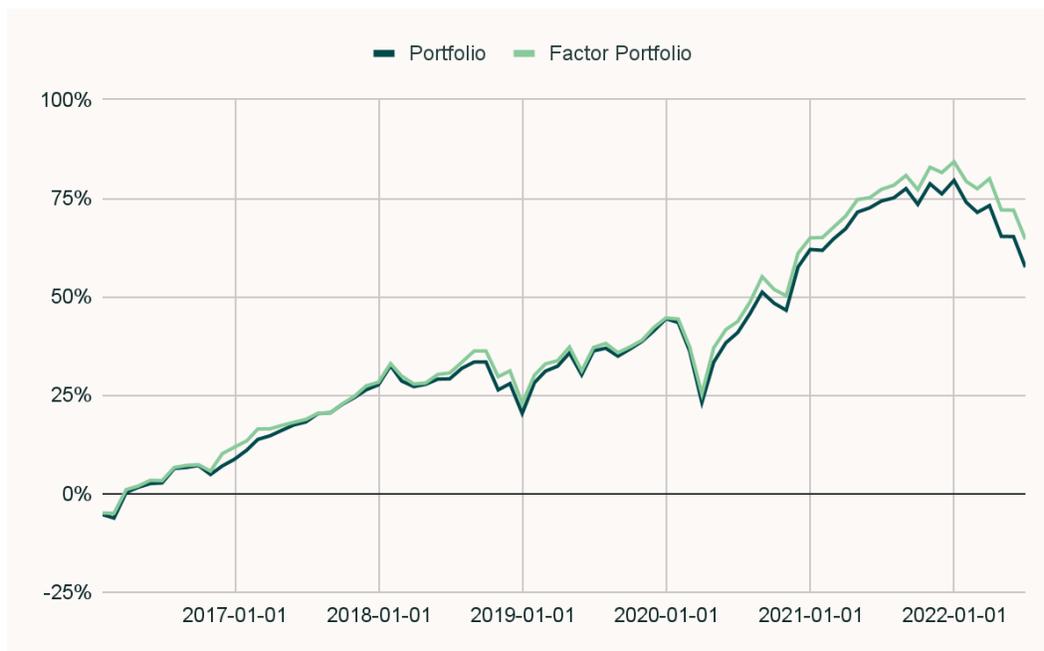
5. Application #3: alternatives—is there beta in your alpha?

If it can be identified, alpha can be a very valuable addition to a portfolio. True alpha, by definition, will be diversifying, and thus provide incremental return with only modest incremental risk (or in some cases, a reduction in portfolio risk). Distinguishing between alpha and beta factor exposures in a portfolio is critical to choosing the right mix of investments.

The problem is that portfolios of alpha may actually be re-packaging market factors (i.e., "betas") as alpha. Factor analysis is one method we can use to help sort out which funds are delivering alpha and which funds are delivering expensive beta. That is, "Is there beta in your alpha"?

As in the previous cases, we begin our analysis by selecting appropriate factors. To keep things simple, we select four basic factors:

- S&P 500 returns
- Index of U.S. Treasury Bonds (7–10 Year)

- Returns from a rolling basket of commodity futures
- Returns from rolling VIX futures

These factors roughly meet our criteria of:

1. Investable—They could all be added (long or short) to a portfolio.
2. Orthogonal—They are very roughly uncorrelated.
3. Applicable—These are factors that an active manager may have exposure to, but are unwanted (because we can source these elsewhere more cheaply and they may contribute significantly to portfolio-level risk).

We note that our model defines alpha as any return that cannot be replicated by these four factors. And these factors are by no means comprehensive. Thus, our alpha may be a blend of missing factor exposure and idiosyncratic manager skill. So, it's probably appropriate to evaluate this analysis as identifying the maximum alpha a manager may be delivering.

Before we look at individual managers, the first question we want to examine is *"Do alternative assets, in aggregate, deliver alpha"?* First, we assemble a portfolio of all of the alternative assets (e.g., PE, VC, hedge funds and CTAs, private debt) on the Addepar platform and generate a return series. We then run a time-series regression against our factors. Lastly, we plot our portfolio's returns against the factor replication's returns with the constant term (i.e., the "alpha") removed.

If alpha is present (as defined by our model), we should see a gap between our aggregate alternatives portfolio and the returns from the factor portfolio (with the constant, representing "alpha," removed).

Factor Replication of Aggregate Alternatives Portfolio

%, Cumulative Return (2016–2022)
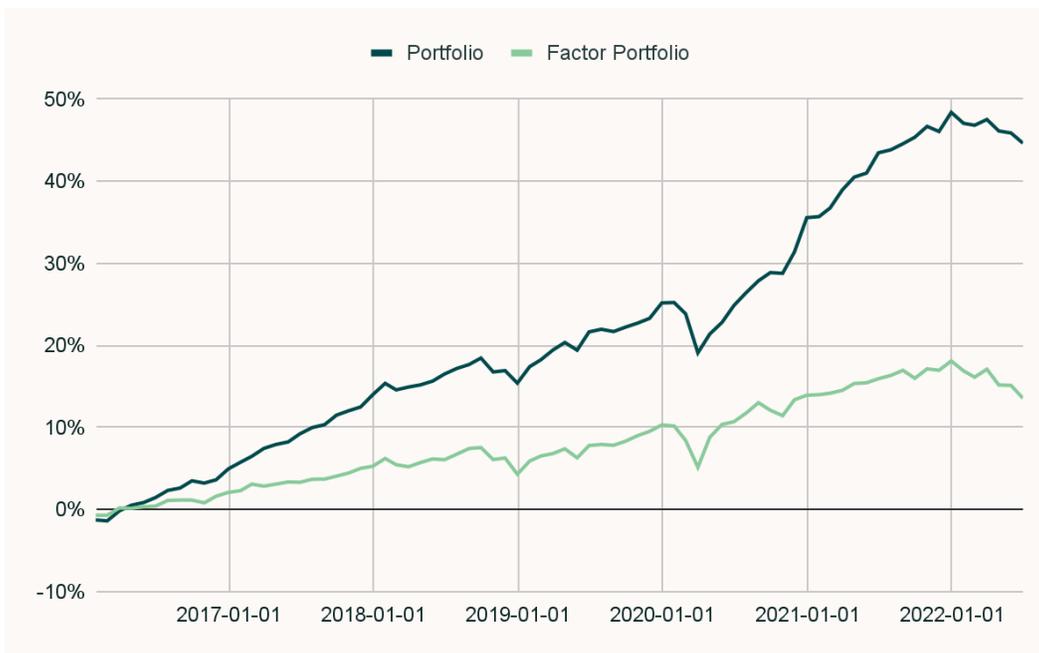
	S&P 500	US Agg Bonds	Constant
Factor	0.22	0.04	0.35%

As you can see, while there's a fair amount of beta in the portfolio, the bulk of the returns appear to be due to the alpha term—that is, manager skill or factors not considered by the model. Now, there's a third set of possibilities in that our return stream may be distorted. Some of the unexplained returns could be the result of either: (1) return-smoothing due to illiquid assets not being priced to market frequently; or (2) the reporting of returns being lagged.

However, putting these issues aside, by and large it appears that there's a fair amount of alpha in the Addepar-wide alternatives portfolio.

Next, we turn our attention to specific managers. We selected four large funds on the Addepar platform and subjected them to the same analysis.

Factor Replication of Mutual Fund A

%, Cumulative Return (1/2017–6/2022)
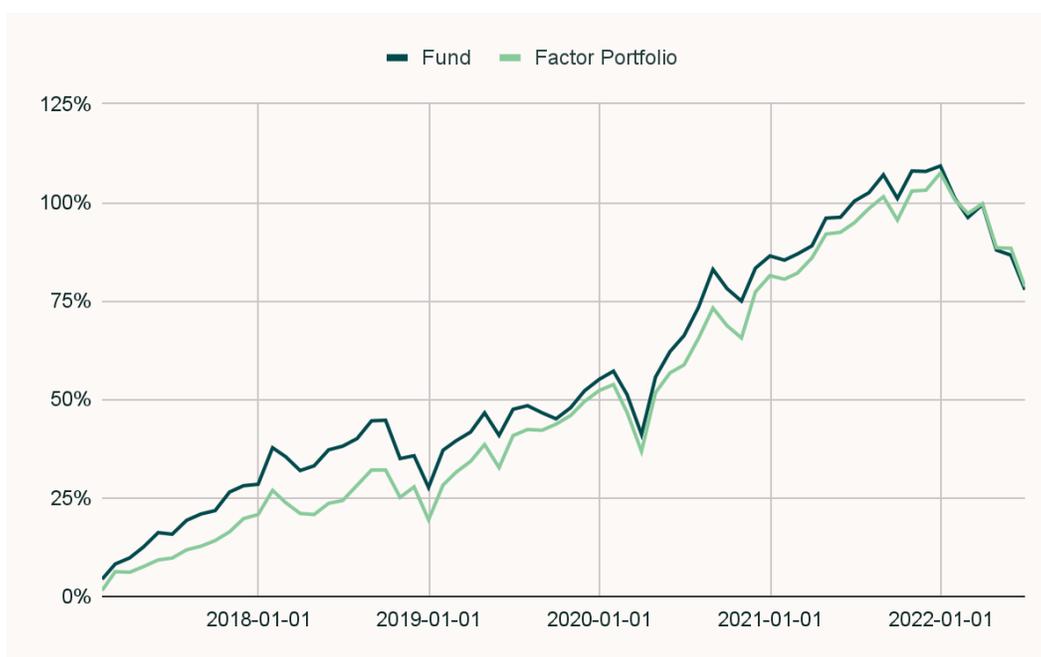
As an illustrative example before we look at three hedge funds, we examine one of the largest actively managed mutual funds. The factor portfolio is able to almost completely replicate the return stream of the fund. There's little alpha present, represented by the gap between the portfolio and the replication. So while the fund is active and fees are higher than what would be found in a passive fund replicating a benchmark, *investors don't appear to receive alpha in return for their fees*.

Factor Replication of Hedge Fund A
%, Cumulative Return (1/2017–6/2022)
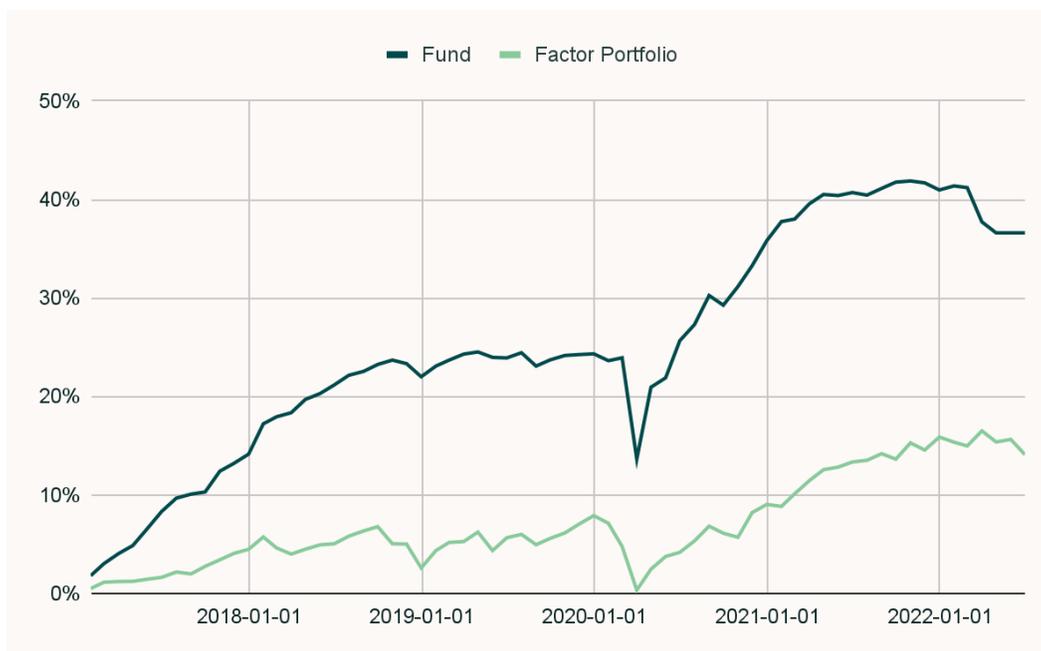
In the analysis above, we see a factor decomposition of the returns of a large multi-strategy hedge fund with a focus on illiquid asset classes. It appears that significant alpha is present, because our factors are able to replicate only a small fraction of the returns. As always, investors need to think critically about the analysis.

In this case, the illiquid nature of the assets may be playing a role in overstating the amount of alpha present. That is, the assets' valuation marks each month may not be indicative of their actual value in the market. And thus, the amount of alpha could be overstated by the model. An assessment of the firm's valuation policy may possibly provide insight into whether this is truly alpha or not. *As always, investor judgment plays a part in assessing what the takeaways of the analysis should be*. However, even with return-smoothing, it's likely that investors are receiving alpha for their fees.

Factor Replication of Hedge Fund B

%, Cumulative Return (1/2017–6/2022)
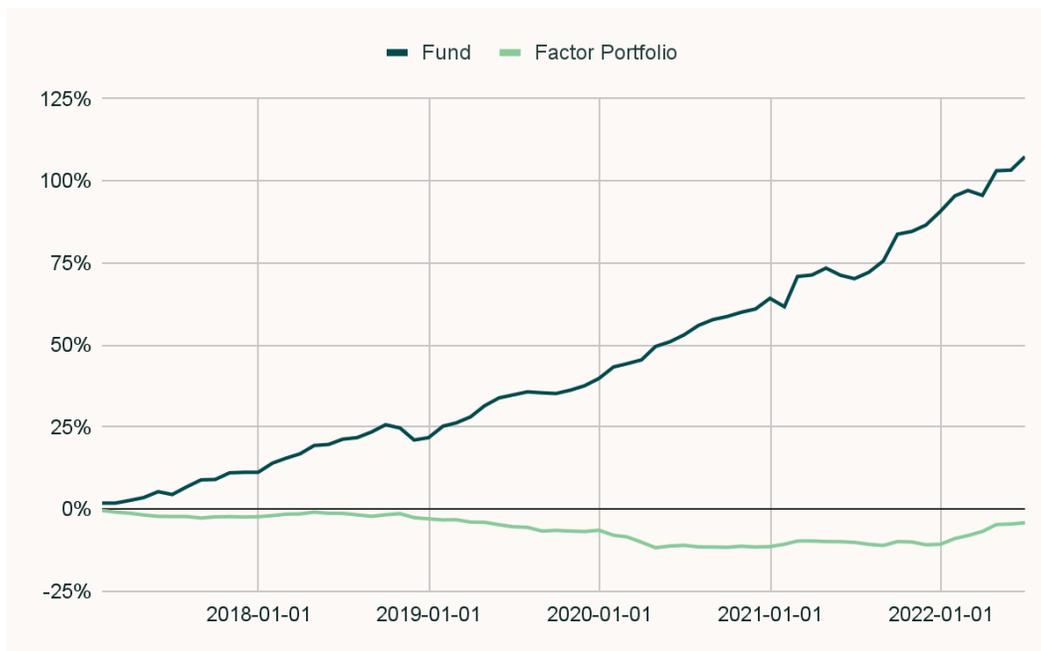
Here, we look at another large multi-strategy fund. In this case, the fund invests primarily in liquid assets, and monthly marks are likely representative of market prices. Our factor model is unable to explain almost any of the performance of the fund. That is, *this return stream is almost entirely alpha (per our model)*. Additionally, the return stream is very smooth, indicative of a high Sharpe ratio (even through the early days of the pandemic). Investors are likely receiving alpha for the fees they're paying and receiving a high-Sharpe return stream.

Factor Replication of Hedge Fund C

%, Cumulative Return (1/2017–6/2022)
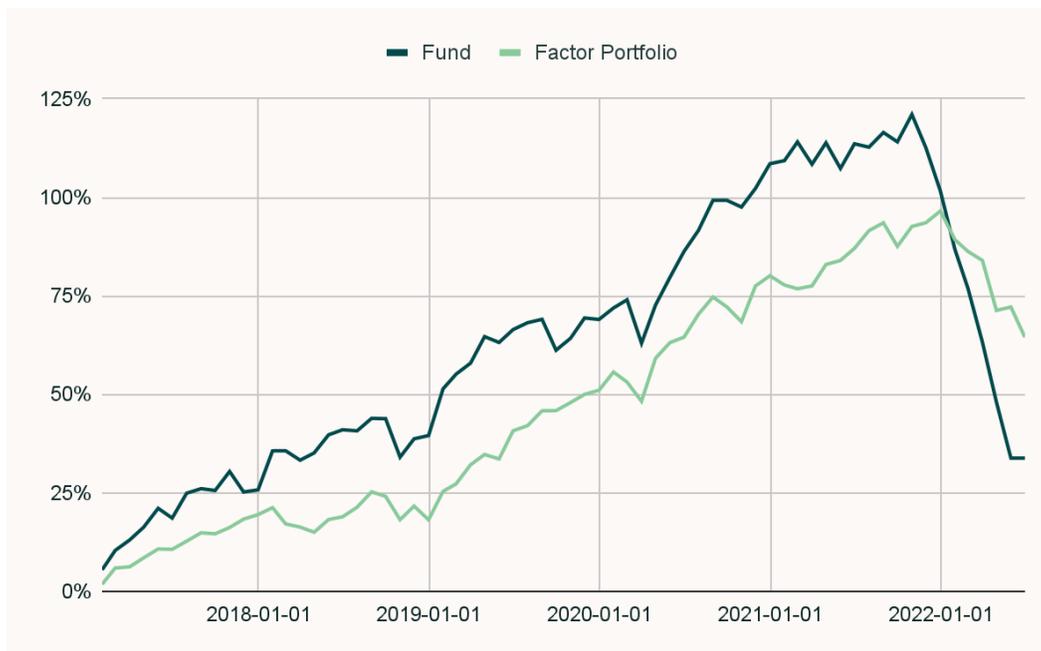
Finally, we look at a long-short equity fund. In this case, our factor model is able to explain a large portion of the fund's returns. There's "beta in the alpha." Additionally, *the cumulative alpha is actually negative*, because the fund's returns underperform the factor-replication model. While the fund appears to accumulate some alpha from 2017 to the end of 2021, it gives it all up and more in 2022. This pattern is indicative of a "selling options" type of exposure. We note that this "picking up pennies in front of a steamroller" pattern would not be indicated by our factor analysis if we only had data between 2017 and 2021. Again, *it's incumbent on investors to consider what might be missing from an analysis and perform the necessary due diligence to augment quantitative assessments*.

	SPY	IEF	GSG	VIXY	Constant
HF A	0.17	-0.13	0.02	-0.01	0.34%
HF B	-0.08	-0.25	0.06	0.00	1.69%
HF C	0.82	1.28	-0.02	0.00	-0.46%
MF A	1.19	0.32	-0.03	0.03	-0.01%

7. Conclusion

Factor analysis is a powerful tool for portfolio construction, capital allocation and attribution. With a few simple factor models, we've shown how investors can identify key risks in their portfolios and assess manager alpha generation. We plan to build on this and perform more comprehensive factor analysis for Addepar clients on an aggregate and individualized basis. If you have questions or suggestions about factor risks in your portfolios or prospective investments, please reach out to the research team at research@addepar.com.

Asset Classifications

Asset class	Sub-asset class
Cash	Cash Cash equivalents
Fixed income	U.S. Treasuries and Agencies U.S. TIPS U.S. investment-grade credit U.S. high yield U.S. bank loans International developed markets Emerging markets Opportunistic Other fixed income Unknown fixed income U.S. municipals/tax exempt
Equities	U.S. equities Global equities Developed markets–Americas Developed markets–EMEA Developed markets–Asia Pacific Emerging & frontier markets Other equities Concentrated equity positions Unknown equities
Mixed allocation	Asset allocation vehicles Held-away accounts
Alternatives	Hedge funds Concentrated alts positions Private equity & venture Real estate funds Other alts Unknown alts
Private business	Direct private companies
Direct real estate	Direct real estate
Other	Collectibles Direct loans Unknown Liability

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