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KEY FINDINGS

- Factor investing is backed by an enormous body of literature, strong out-of-sample evidence, and an economically intuitive rationale.
- Factor investment strategies provide valuable diversification to traditional markets that is not dependent on market conditions or macroeconomic environments.
- Factor timing is difficult, and a consistent and disciplined exposure to a well-diversified multifactor portfolio is hard to beat.

ABSTRACT

Factor investing has been around for several decades, backed by an enormous body of literature, and yet it is still surrounded by much confusion and debate. Some of the rhetoric and myths have existed for a long time, while others have arisen in response to the difficult performance from 2018 to 2020 and the subsequent turnaround. This article examines many claims about factor investing; some are timeless, while others are focused on specific concerns that have emerged recently. The authors reference an extensive academic literature and perform simple, yet powerful, analysis to address these claims.

Factor investing has been around for a long time and an immense literature in academia and practice is devoted to it. Yet, much confusion about it remains. We have written about the facts and fictions of specific factor investing styles—namely, value, momentum, low risk, and size.[1] Here, we finish the series reviewing the facts and fictions surrounding a general factor and multifactor investment approach.

From 2018 to 2020, an extreme drawdown in many implementations shook investors' belief in and spawned myths about multifactor investing. Following the drawdown, a rebound—albeit a sometimes rocky one—began in 2021 and continued into 2022. In some cases, this recovery period quieted the critics, and in others, it exaggerated certain myths. Our aim is to focus on the long-term properties of factor investing while addressing what can be learned about investor behavior from extreme, short-term swings in performance.

For example, even the authors' own publication behavior can be affected by recent events. Full disclosure: We intended to write this article in 2019, but being known proponents of factors, we balked at the risk of looking like we were just trying to excuse recent events. One of the topics we will cover is that drawdowns can take an excruciatingly long time and can therefore have consequences on investment (or in

[1] See Asness, Frazzini, Israel, and Moskowitz (2014), Asness, Frazzini, Israel, and Moskowitz (2015), Alquist, Israel, and Moskowitz (2018), and Alquist et al. (2020).

this case publication) behavior, even for those who believe in the long-term efficacy of these strategies.

The issues we tackle here have been around for far longer than the recent drawdown and are, in some cases, timeless. And, while myths often resurface during extreme times and some never seem to fully die, they are also important considerations when thinking about factor investing. These myths are often proclaimed by those who do not use or embrace factors but are also sometimes voiced by those who do.[2] Our dual aim is to clarify truths and address misconceptions but also to understand why confusion and flawed beliefs continue to arise.

Before proceeding, it is useful to define factor investing. We define it as a systematic tilting toward a style/theme (and away from its polar opposite) implemented across a diversified set of assets. These tilts deviate from market weights and can be implemented in long-only or long–short portfolios. The themes or factors originate primarily from academia, motivated by economic theory and empirical study. Although we focus on systematic versions of factor implementations, discretionary investing into factors, even if only implicit, is also possible and relevant, where the same ideas and misconceptions apply.

We focus on the main factors that pervade the academic literature and practice: value, momentum, carry, and defensive/quality investing. These factors dominate the empirical models used in academic finance. In doing so, we will also try to use data readily and publicly available from academia that uses simple, replicable measures. While these simple strategies may be naïve in design (e.g., ignoring transaction costs, explicit risk management, tax, and other considerations), they nicely illustrate the basic ideas and can be easily replicated. Moreover, we will then cover practical implementation tweaks to the factors that can improve returns, reduce risk, and lower implementation costs. As in our previous articles, we address the facts and fictions of factor investing using published and peer-reviewed academic papers and conduct tests using the most well-known and straightforward publicly available data.

EXAMINING THE FACTS AND FICTIONS

We proceed to tackle the following 10 facts and fictions associated with factor investing.[3]

1. *Fiction*: Factor investing is based on data-mined factors with no good economic story.
2. *Fact*: Factors are risky.
3. *Fiction*: Factor diversification often fails when you need it the most.
4. *Fact*: Factors work across many markets and conditions.
5. *Fiction*: Factors do not work anymore in the new economy.
6. *Fact*: Factors were not and are not too crowded, despite being well known.
7. *Fiction*: Everyone should invest in factors.
8. *Fact*: Factor discipline generally trumps timing, tinkering, and trading.
9. *Fiction*: You know when you are in a drawdown/recovery and when to cut/add risk.
10. *Fact*: Sticking with factor investing is hard, but worth it.

[2] See "Alice's Adventures in Factorland: Three Blunders That Plague Factor Investing" (February 2019), by Rob Arnott, Campbell Harvey, Vitali Kalesnik, and Juhanni Linnainmaa, online at https://www.researchaffiliates.com/publications/articles/710-alices-adventures-in-factorland-three-blunders-that-plague-factor-investing.

[3] We could choose to describe something as a "fact" or "fiction" at will (e.g., instead of #5, say "Fact: Factors still work in the new economy"). We choose the framing we think most intuitive but recognize it is an arbitrary decision.

#1. *Fiction*: Factor Investing Is Based on Data-Mined Factors with No Good Economic Story[4]

Social sciences, particularly those that examine the same or similar data repeatedly, are subject to the criticisms of data mining and overfitting. Because any sample of data contains both truth and error, this raises the concern that an over-examination of such data can lead to many "fitting errors" rather than truth. This results in false discoveries—patterns found in the data that are not real but rather aberrations found by random chance.

The academic finance literature is replete with a host of factors claiming to predict returns, which seems surprising given the general efficiency of markets. As such, critics often accuse our field of false discoveries, that is, factors that are not real but rather found by chance in the same sample of data researchers have been mining for decades.

An often-cited critique of factor investing—an implementation of factor research—is that it is based on data-mined factors, with no good economic story. It is, of course, an extremely valid concern. Indeed, one way to combat this critique is to consider the theory behind a factor (and perhaps an earlier step is to have *any* theory behind a factor). *Why* does a factor generate abnormally positive returns? A random false discovery will not have a logical reason behind it. Theory, on the other hand, provides a disciplined guide to examining data because it provides guard rails to prevent overfitting.[5] Anything outside of the model is treated as noise and cannot therefore be falsely discovered.

There are other assessments of factor validity besides theoretical backing, including out-of-sample evidence and formal statistical tests, that also address the overfitting concern. We will discuss these as well, but first we start with the economic theory behind factor investing and, more specifically, behind some of the main factors used in practice.

Economic theory. The theory underlying factor investing is that there are more dimensions to building efficient portfolios in practice than simply taking on market risk. Certain factors deliver positive returns beyond market risk either because they offer compensation for an additional risk exposure in efficient markets that some investors care about or because they exploit or take the other side of different preferences or beliefs some investors have. The former is characterized as risk-based explanations for factor investing, motivated generally by classic theories such as Merton (1973) and Ross (1976) that give rise to multiple factors beyond the market providing risk premia or sources of positive expected returns to investors. The latter is characterized by behavioral explanations that focus on preferences or beliefs that deviate from classic wealth-maximizing objectives and hence create pricing deviations from risk compensation alone (e.g., Fama and French 2007; Shleifer 2000; Thaler 2003; Barberis 2018). These can be errors consistent with behavioral economics or simply tastes for something other than the highest risk-adjusted return.

Importantly, both sets of theories—risk based and behavioral—provide a role for factors to deliver consistent positive expected returns beyond the market. However, an economic rationale is not sufficient alone to justify the premium. Two additionally important (and related) considerations are to ask why the premia do not get arbitraged away and, related, is there a sustainable set of investors willing to take the other side of these factor trades?

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[4] This first section is by far our longest as it introduces the data and many of the concepts needed for the rest. We mention this so readers do not give up assuming nine more of these to go!

[5] Of course, this is a level of protection from data mining not a panacea. If one comes up with "iffy" theories only after observing the data, the dangers of data mining might not be mitigated.

The only portfolio every investor can hold simultaneously is the market portfolio because it is the aggregate of all investor positions. As such, any deviation from the market, such as investing in factors, must be met with someone's willingness to take the other side. So, for example, for every value investor who likes and overweights cheap stocks relative to expensive stocks, there must be another investor who is willing to underweight cheap in favor of overweighting expensive stocks.

This idea of "who is on the other side" (Ilmanen et al. 2022) is an important consideration for understanding the source of returns associated with a factor and hence why one would expect such returns to persist. Continuing the cheap versus expensive stocks example, if everyone decided they wanted to overweight cheap stocks and no one was willing to meet that demand, then the price of cheap stocks would rise, and they would cease to be cheap. These dynamics represent the process of arbitrage that would eliminate any source of returns from buying cheap stocks going forward. An important question, therefore, is why these factors do not get arbitraged away.

The risk-based and behavioral explanations provide a rationale for why some investors continue to take the other side and are likely to continue to do so. Under the risk-based view, cheap stocks are cheap because they are indeed risky—they are exposed to a source of risk some investors do not like and do not wish to own. Implicit in this view is that dislike of this risk is rational—otherwise it would be in the behavioral category.[6] Consequently, an investor willing to bear this risk will earn a return premium to compensate her for bearing this risk, and another investor who does not want this risk is willing to "pay" to avoid it, by not owning the cheap stocks. The behavioral explanations work similarly, in that investors whose preferences or beliefs cause them to like cheap stocks earn returns at the expense of investors whose preferences align with expensive stocks.[7] For example, cheap stocks may be in old, boring technologies that do not exhibit the lottery-like payoff potential or exuberance of new technology growth firms. If some investors clamor toward the new growth firms, driving up their price, then investors willing to hold the boring value firms will get them at a cheaper than justified price and earn higher returns.

Exhibit 1 provides a brief summary of some of the risk-based and behavioral theories offered for the most prominent factors from the literature that are used in practice. The theories also offer an explanation of who is on the other side of each factor, presented in the last column of the exhibit. As discussed in the introduction, we focus on the main factors that dominate the academic and practitioner landscape: value, momentum, carry, and defensive/quality.

Risk-based theories for the factors offer different dimensions of risk in the economy unrelated to general market risk. For example, the value premium may be compensation for distress risk (Fama and French 1993) or duration risk (Lettau and Wachter 2007; Gormsen and Lazarus 2021). The momentum premium may be due to inherent crash risk associated with the strategy that is tied to the option-like exposure of the strategy to market risk (Daniel and Moskowitz 2016). The carry premium may be compensation for bearing spot exchange rate crashes and extreme skewness in currency returns (Brunnermeier, Nagel, and Pedersen 2008). Defensive or quality strategies also may be exposed to duration risk and funding liquidity shocks (Gormsen and Lazarus 2021; Frazzini and Pedersen 2013). In the next section, we take an

[6] Of course, "rational" requires a model of what is rational—the famous "joint hypothesis" problem that comes with trying to test the efficient markets hypothesis.

[7] Again, the difference is in this case we cannot find a rational equilibrium model that aligns with these beliefs (or misbeliefs) or preferences.

EXHIBIT 1
Style Groups and Rationales

Style Group	Behavioral/Risk-Based Rationales	Who Is on the Other Side?
Value	• Over-extrapolation of past growth • Discomfort with 'dogs'/boring companies or old tech • Distress risk • Duration risk	• Multi-year return-chasers • Investors attracted to glamor stocks • Investors averse to some risks in value stocks
Momentum	• Underreaction to news • Delayed overreaction to price trends • Crash risk • Disposition effect	• Contrarians resisting the herd • Investors realizing gains or hanging on to losers • Investors averse to crash risk in momentum assets
Carry[a]	• Premium for skew/jump risk/bad times losses • Capital supply/demand imbalances • Non-profit-driven flows	• Tail insurance buyers • Overconfident holders of salient macro views • Non-profit-driven actors, for example, central banks • Liquidity-demanding investors
Defensive Low Risk Quality	• Leverage aversion/constraints • Lottery-seeking preferences • Under-appreciation of quality characteristics	• Leverage-constrained or leverage-averse investors • Investors who prefer lottery-like upside

NOTES: [a]Volatility premia and illiquidity premia are also factors with carry-like characteristics that have good theory behind them and a natural holder of the other side. We refer here to carry strategies in general, which can be applied to all asset classes (e.g., Koijen et al. 2018). We focus on the factors we have written most about, that seem to dominate most portfolios, and for which we can supply the longest data.

empirical look at the actual risks of these strategies viewed in isolation,[8] and we show that each factor can suffer at times from prolonged drawdowns and infrequent, but extreme, underperformance.

In short, factor investment strategies are hardly arbitrage opportunities.[9] They provide long-term positive expected returns but occasionally suffer from severe short-term poor performance, or bad medium-term disappointment, or even long-term futility.[10] Risk-based explanations require that these risks actually materialize and cannot be avoided—if they could be avoided, they would not be risky—and often, that they hurt when it hurts most to be hurt! In fact, these theories state explicitly that without experiencing these risks, there would be no premium. So, while living through these risks is not pleasant (see the next section), a long-term investor should take solace in the fact that the risk itself implies there should be a premium over time.

The existence of these (undiversifiable and/or coming at the most painful times) drawdowns is also what determines who is on the other side of each of these factor strategies. Investors who cannot stomach the short-term downswings in these strategies may be willing to forgo the added long-term expected return premium associated with the strategies in order to avoid these risks. In this way, factors can be thought of as insurance or hedging portfolios that allow investors who do not want exposure

[8]We note that while an important part of the practical story, just the fact that a factor can suffer greatly does not mean it truly represents "risk" in the first (nonbehavioral) sense. Risk in this first sense indeed involves loss but loss that is exceptionally likely in, say, periods of distress for the overall portfolio (so undiversifiable loss) or, often related, periods where the marginal cost of loss is quite high to the representative investor.

[9]We remind readers of Asness's (2014) Peeve #5: that the practical investment world often redefines arbitrage from its academic meaning of riskless profit to "a trade we kind of like."

[10]See Asness (2021).

to these risks to pay a small premium (in the form of selling at discounted prices) to investors willing to bear them. This story provides a nice equilibrium where factors earn long-term returns due to a natural supply and demand for bearing risk.

The behavioral explanations, in turn, also provide a natural set of investors on the other side of factor trades. For value, excitable investors chasing recent growth trends and clamoring to buy up the latest growth and tech firms will pay a higher price to those investors who do not mind holding the old technology/boring companies (Lakonishok, Shleifer, and Vishny 1994; Piotroski and So 2012). For momentum, contrarian investors who resist the herd at a shorter horizon than for value or those who suffer from the disposition effect (Frazzini 2006) take the other side. For carry, investors with objectives other than profit maximization (e.g., central banks, governments) may be willing to take the other side. And, for defensive, investors who seek lottery-like returns—high payoffs with low probability—and who may be leverage-constrained (Frazzini and Pedersen 2013; Barberis, Jin, and Wang 2021) pay a higher price to those investors who can borrow cheaply or who do not desire lottery-like payoffs.

Of course, these explanations are not mutually exclusive. A premium associated with a factor can be driven by both risk and behavioral forces. The important point is that both sets of theories give a solid economic rationale for why a premium exists and is expected to continue to exist often with testable or observable implications behind simply looking at returns. Moreover, the changing risk appetite and/or preferences and beliefs of investors over time can give rise to variation in the size of these premia. An open question is whether such variation can be measured or predicted, a topic we address in fact #4 of this article.

Besides theory, formal statistical tests and out-of-sample verification can also assuage data-mining/overfitting concerns.[11]

More rigorous statistical tests. A recent literature has emerged in finance that criticizes the plethora of factor discoveries made in our field, arguing that more rigorous statistical tests should be conducted that adjust for data mining. Harvey, Liu, and Zhu (2016) document more than 300 factor discoveries in the literature and claim that many of them would not pass a more stringent statistical threshold that accounts for multiple testing (i.e., data mining). They suggest using a statistical threshold with a *t*-statistic of at least 3 to reduce the number of false discoveries. Hou, Xue, and Zhang (2017) examine more than 400 empirical anomalies in finance and argue that many are not replicable or robust to small specification changes. Feng, Giglio, and Xiu (2019) and Freyberger, Neuhierl, and Weber (2020) propose machine learning techniques to screen factors that account for overfitting and other biases.

To account for the pernicious effects of data mining, these papers raise the statistical hurdle for significance. For instance, the standard *t*-statistic threshold of 2.0 for a single hypothesis test gives the researcher roughly 95% confidence that the result is not a false discovery. However, if the researcher ran more than one test (e.g., data mined), the chances of finding at least one *t*-stat of 2.0 become greater. How many tests would a researcher need to run if they wanted to almost guarantee (99.9% likely) finding at least one *t*-stat above 2? The answer is 121 (independent) tests. That is, if a researcher ran 121 random, independent tests on a set of data, you would all but guarantee finding at least one false discovery. That may not seem like a lot of tests when you consider all of the research in academia and in practice searching for positive trading strategies on the same data. Conversely, there is much

[11] Out-of-sample verification can look at time periods (e.g., we have 30+ years of additional evidence since the early academic work on value and momentum) or other assets classes/geographies (Fama and French 2012; Rouwenhorst 1998, 1999; Griffin, Ji, and Martin 2003).

overlap among such research—that is, separate tests need not be independent.[12] In any event, by upping the statistical threshold to, say, a *t*-stat of 3.0, the number of (independent) tests one would need to run to guarantee a false positive jumps to 393. With a *t*-stat of 5.0? 408,234. A *t*-stat of 8.0? 439,976,957,014—nearly half a trillion! So, when it comes to data mining concerns, the strength of the statistical significance matters. We probably (there are exceptions) are not too concerned with data mining when we see a *t*-stat of 8.0, but we might worry a lot about a *t*-stat just above 2.0.

All of these papers raise the bar for statistical significance and thus reduce the number of reliable factor discoveries, calling into question some previous results. However, these papers also show that many factors pass these more stringent statistical tests. The factors associated with value, momentum, carry, and defensive/quality seem to qualify, for instance. In fact, many of the loudest critics have their own factor models, which largely consist of variations of these same canonical factors. Hence, the critics do not disavow factors at all, but rather, quite reasonably, want a more rigorous selection procedure for which factors matter. When applying these more stringent statistical criteria, factors such as value, momentum, carry, and defensive/quality still emerge as significant and reliable factors.[13]

Out-of-sample evidence. Perhaps the best and most compelling way to combat the data-mining critique is to provide evidence outside of the original sample in which these factor-based strategies were discovered. Because errors are random, if research overfits errors by data mining in the original sample, then when applied to a new, independent sample, these strategies would cease to yield significant results. There are several ways to find out-of-sample evidence, including other time periods from the original sample,[14] other markets not studied originally, and other asset classes.

McLean and Pontiff (2016) examine the out-of-sample evidence of 98 factors using the time since publication of the original studies that discovered them. They find a roughly 25% decline in performance from the original sample, suggesting perhaps some overfitting in the original sample. They also find a 32% decline in performance that they claim is due to arbitrage activity—a topic we address later. However, their results also highlight that a significant percentage of the performance remains out of sample, indicating that many of these factors are real and generate significant returns, albeit less than claimed from the original samples.[15]

Ilmanen et al. (2021) examine the out-of-sample performance of the main factors we focus on—value, momentum, carry, and defensive—using a century of data across multiple markets and asset classes. They analyze the performance of these factors across US stocks, global stocks, equity indices, currencies, fixed income, and commodities and use data both *before* the original sample started ("pre-sample" evidence) and after the original sample ended ("post-sample" period). Exhibit 2 highlights the results from their study, which shows that these factors work uniformly

[12] Independent is a key word here that often does not get enough emphasis. Many of the myriad of factor tests conducted in published papers are on variations of a few central themes and are not close to independent.

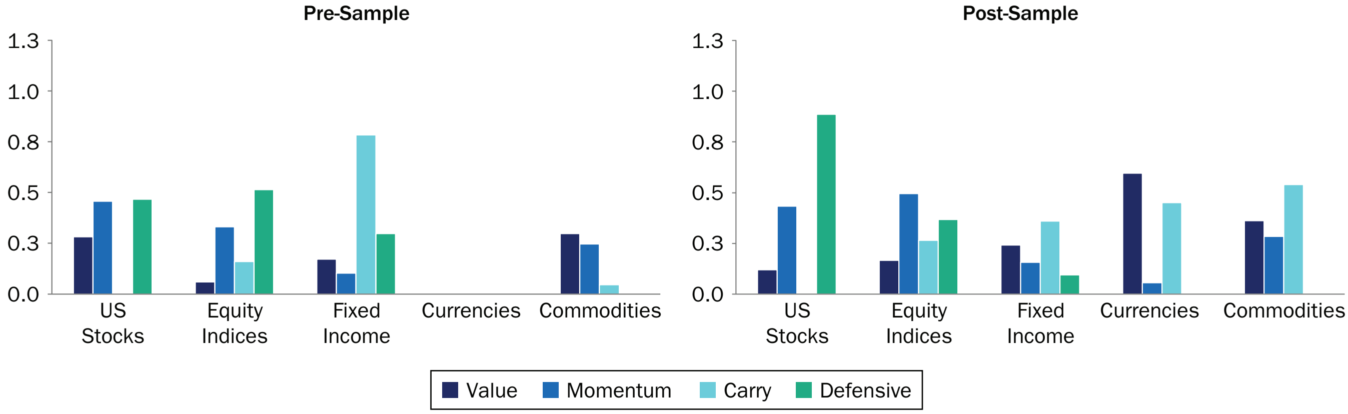
[13] For a debate on this issue, see "Lies, Damned Lies, and Data Mining" by Cliff Asness (April 12, 2017) online at https://www.aqr.com/Research-Archive/Perspectives/Lies-Damned-Lies-and-Data-Mining.

[14] One must take care to consider what length of out-of-sample period is adequate, given that a factor with a Sharpe ratio of 0.3, for example, can experience a tough decade with high probability (you need a standard deviation event of only about –1 to make nothing for a decade).

[15] In fact, some practitioners who shall remain nameless (many, including us), have used significant discounts to back tests in forming expectations for future factor performance for at least several decades.

EXHIBIT 2

Hypothetical Sharpe Ratios across Factors and Asset Classes (January 1920–August 2022)



NOTES: For currencies, we have no pre-sample period because exchange rates were pegged under Bretton Woods prior to 1973 (Accominotti and Chambers 2014 find positive carry and momentum returns in currencies in the 1920s and 1930s that precede the fixed rate regime of Bretton-Woods, providing additional out-of-sample evidence). A defensive strategy for currencies is not shown because there is no logical market index. A defensive strategy for commodities is not shown either because returns from different commodities do not share a common market component. A carry strategy for stock selection is not shown because it is nearly identical to a value strategy in stock selection.

across all markets and asset classes and their performance is stable over the periods before and after the original sample period, with little degradation from the original sample period. These facts provide strong out-of-sample evidence on the efficacy of these factors that diminishes data mining concerns. Of particular note is the strong evidence of factor returns before the original samples, indicating that these factors delivered strong sources of returns well before researchers studied them or even conceived of them. And the fact that their performance is similar in the post-sample period after discovery strongly suggests that these strategies are not the result of data mining and are unlikely to have been arbitraged away.

For simplicity and because their data is publicly available, we will use the time series of factor returns from Ilmanen et al. (2021) throughout this article, unless otherwise noted. Although their factors are not optimized in any way and can be improved upon in practice through diversification across different measures of the same phenomenon and other design choices that improve implementation efficacy, they represent simple, replicable factor series that capture the premia well (although before transactions costs).[16]

Finally, a recent paper by Jensen, Kelly, and Pedersen (2021) questions whether there really is a replication issue in our field with their shockingly titled paper "Is There a Replication Crisis in Finance?" In their paper, the authors first point out that the supposed large number of factors people claim (e.g., 400+) is grossly exaggerated, as many of these factors are somewhat different versions of the same theme. For example, there are more than 80 versions of value signals that are all highly correlated (e.g., book-to-price ratio vs. earnings-to-price ratio are not very different), and dozens of measures of momentum. These should hardly be treated as independent factors. More accurately, there are not hundreds of factors but perhaps dozens of factor themes. The authors propose a factor taxonomy that algorithmically classifies factors into themes possessing a high degree of within-theme return correlation and similarity of economic concept.

[16] Factors are constructed long–short gross of implementation costs.

Second, Jensen, Kelly, and Pedersen employ a Bayesian framework to evaluate the out-of-sample performance of these factors. They make the point that a prior of zero alpha, which is a reasonable prior if markets are efficient, would imply that an investor *should* expect lower out-of-sample performance, because returns should shrink toward that prior as the truth is some combination of theory (e.g., one's prior) and data (measured with error). This suggests that positive but lower out-of-sample performance should be expected and not necessarily viewed as evidence of overfitting.

Third, Jensen, Kelly, and Pedersen also examine the factors together, combined into one portfolio. This accounts for the fact that factors provide diversification benefits (a topic we cover later), and that perhaps a better and more robust way to look at factor performance is to look holistically at the mean-variance efficient portfolio of all factors. The performance of the tangency portfolio of factors fares even better out of sample, as diversification across factors mitigates noise in each of the individual factors.

Examining a portfolio of factors is also a useful way to assess the data mining issue. For example, consider an equal-weighted portfolio of value, momentum, and defensive/quality factors applied to US individual stocks. Such a portfolio has a backtested Sharpe ratio of 1.1 with a *t*-statistic of 10.8, as documented by Ilmanen et al. (2021) using data from 1926 to 2020. As discussed earlier, data mining would have a hard time explaining a *t*-stat of nearly 11—it would take nearly a trillion random trials to get a *t*-statistic that large! Now, applying those same factors across markets and asset classes (and adding carry as well), the same authors find an annualized Sharpe ratio of 1.5 with a *t*-stat of more than 14! That amount of statistical significance, coupled with out-of-sample evidence from other markets and asset classes, casts serious doubt (read: astronomical odds) on data mining driving the significance of these factors.

Not all factors are created equal. We have already touched upon the idea that there are not really 400+ factors discovered in academia, but rather several dozen factor themes containing slight variations of measuring the same concept. But, even among these themes, not all factors should be treated equally. For example, a factor with stronger in-sample statistical significance, stronger out-of-sample evidence, and a better economic story should be given more credibility (and more weight in a quantitative model). Many proposed factors in the literature have weak economic motivation, barely pass a low statistical hurdle (e.g., *t*-stat of 2), and may therefore have, unsurprisingly, poor out-of-sample performance. When looking across factors, the ones with better economic stories and stronger statistical reliability indeed have better out-of-sample performance. This is not a coincidence, but the outcome of solid science.

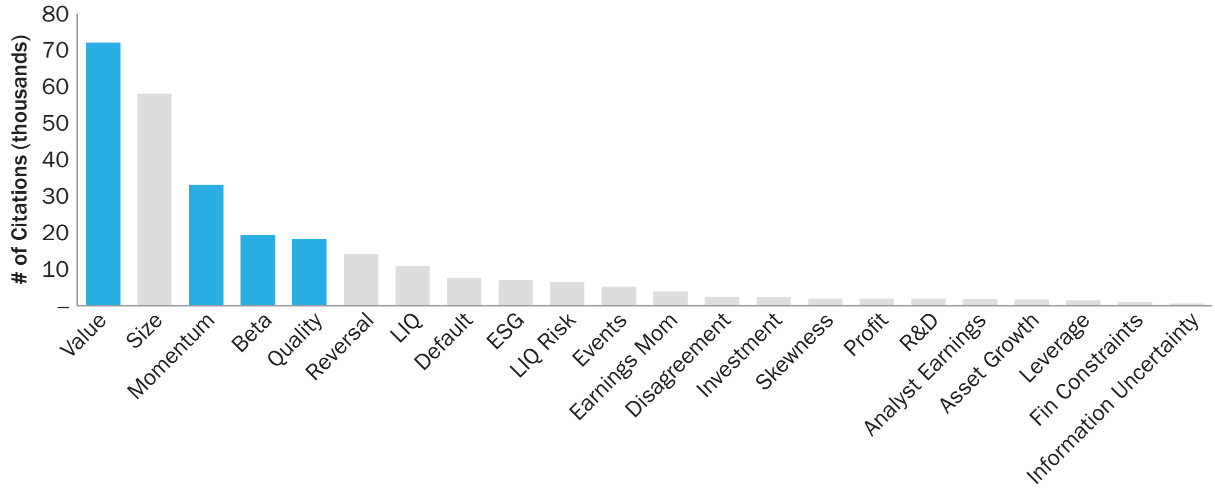
And academia has understood this. Despite the explosion of factor discoveries and the abundance of factors critics have pointed to as evidence of data mining, the number of factors researchers in academic finance routinely use is quite small. For example, the leading factor models used in finance contain only a handful of factors, such as the Fama and French (2015) five-factor model or Hou, Xue, and Zhang's (2015) four-factor model. The field has simply not adopted a 400-factor model. The scientific community agrees there are not 400 factors.

More interestingly, the factors that have received the most attention in academia are precisely those that satisfy the three criteria we have espoused for determining the reliability of a factor: solid economic theory, strong in-sample statistical significance, and consistent out-of-sample performance.[17] To back this statement up,

[17] One can, however, not be too greedy about consistency. For reference, the US equity premium had three negative decades over the past century (around the 1930s, 1970s, and 2000s). Similarly, factor investing may sometimes require patience to reap the long-term rewards. Additionally, if one cuts the data finer and finer (e.g., analyzing performance across regions), the ex-ante chance that one factor strategy in one region has delivered historically poor results increases (see Asness 2011).

EXHIBIT 3

Numbers of Citations (in thousands) by Factor



we use Google Scholar to document the number of academic citations pertaining to papers written about each factor.[18] Exhibit 3 graphs the number of citations (in thousands) by factor. The chart shows that the most cited factors by far are value, size, momentum, defensive (beta and quality) factors. Those factors, not coincidentally, also have the best economic stories, strongest statistical evidence, and consistent out-of-sample performance. Put differently, if one thinks of citations as the currency of the academic market, "academic market prices" of these factor discoveries are perfectly aligned with their veracity and reliability. In other words, the (academic) market understands what a reliable factor is and, conversely, what it is not. In this sense, the idea that there is a replication crisis in finance or that our field has not learned anything about what drives expected returns is way (waaaaay!) overblown. The reality is that most of the work in academia focuses on factors for which there is consensus.

Academia is not the only market that recognizes that the most "real" factors are those with some degree of consensus. In practice, most quantitative firms also focus on the same factors, albeit each fund manager may measure these factors slightly differently, adding their own, perhaps proprietary, ways of measuring them and perhaps disagreeing about one or two of the major factor categories.[19,20] Practitioners use the same criteria of economic intuition, statistical evidence, and consistent out-of-sample performance to identify the right set of factors. However, they also will add another criterion, which is practical implementation. When faced with real-world frictions, such as trading costs, leverage and risk constraints, liquidity issues, etc. some factors may prove too costly to implement or less attractive after taking into account these implementation costs. For example, factors associated with size,

[18] Given that most of the literature focuses on individual equity factors, we only examine those factors, which are also the set of factors that critics of this literature focus on. Again, factor investing can be used for many other investing decisions.

[19] Many reasonable approaches will arrive at slightly different versions of the same factor set being used, with substantial commonality among them. While fund manager *A* may debate that their factor measure is better than manager *B*'s, often over-emphasizing their differences, they often miss the bigger common picture that they are measuring the same thing. That is not to say that details are not important, but these debates should not lose sight of the bigger picture on the efficacy of factors in general—we all agree that value is a valid and useful investment factor.

[20] See Esakia et al. (2019), Asness (2020), and Blitz and Hanauer (2021).

short-term reversals, and illiquidity look a lot weaker after accounting for such costs. Hence, adding practical implementation considerations reduces the number of viable factors even further.

Applying all of these criteria, we find that factors associated with value, momentum, carry, and defensive/quality survive, as highlighted in blue in Exhibit 3. Not surprisingly, these same factors are the most common among quantitative investors, and thus we focus on them in this article.[21]

Fact within the fiction: Research focused on understanding is just as important (maybe more so) than new research in search of new factors. As mentioned, important ways to combat data mining are having good theory and solid out-of-sample evidence. Ongoing research furthering that objective is therefore valuable to provide confidence that factors deliver long-term positive expected returns. Supporting confidence in existing factors is still an important research agenda, as important as discovering new factors. Research into existing factors is often overlooked, as most researchers—in academia and practice—want to search for new ideas and new sources of returns. That search, while valuable, is also difficult (markets are pretty darn efficient) and fraught with error (overfitting). Finding new support for existing factors is valuable and perhaps easier and less prone to error. It can also lead to better performance, too. For example, discovering a better economic story for a factor not only provides greater confidence in that factor's efficacy but also might inspire a better way to measure it. Such innovations can be considered forms of proprietary alpha, where the factor may be generally known, but a proprietary way of measuring or capturing it may give a manager an edge.

Furthermore, as we will discuss next, factors will almost surely suffer through bad times. Being able to stick with short-term drawdowns, in order to reap the long-term returns associated with a factor, requires a level of faith and confidence. Research into understanding a known factor, especially during its tough times, can be invaluable in helping you stick with it. That research can help you understand that the economic story underlying the factor has not changed, or that the drawdown is a "natural" part of the strategy and not an indication that the world has changed. In fact, such understanding can be reassuring that the premium you expect to earn from the factor is precisely because of the pain you are experiencing now. Of course, it is also possible to learn that the world has indeed changed, in which case an investor might engage (hopefully carefully!) in factor timing or tactical tilts—a topic we cover later. Hence, research into known factors is a vital and ongoing process that can help you better stick with it to maximize its benefits, measure and capture it better to improve performance, or identify regime changes and benefit from timing. We discuss each of these issues in the remainder of this article.

#2. *Fact*: Factors Are Risky

Multifactor investing boasts a strong, long-term track record, and in particular, until 2018, it enjoyed an almost decade-long heyday in both performance and popularity. In some ways, these halcyon days may have given some investors a false sense of security, despite the fact that factors' riskiness has long been well documented in

[21] The only exception is the size factor. While heavily documented in the academic literature and part of the three- factor Fama–French model, we do not have conviction in its long-term efficacy. As explained in Asness et al. (2015) and Alquist, Israel, and Moskowitz (2018), we lack conviction in the size factor for multiple reasons: its weak historical record especially post discovery, its being driven mainly by extreme shocks, its concentration in January, its lack of robustness across definitions and geographies, and its being subsumed by proxies for illiquidity. In addition, this factor is hurt most by transactions costs and illiquidity issues and is not easily applied outside of equities (i.e., what is the "size" of a currency?).

the academic literature (see fiction #1). As alluded to earlier, part of a factor's long-term premium may come with the potential for short-term pain. Risk-based theories for factor premia *require* such painful periods. Behavioral theories may also give rise to tough times as sentiment may continue to move in the same direction before markets correct. After all, if you are trading on what you think are others' errors, it is difficult to put a firm limit on how large those errors can become. In both cases, the economic theory behind factor premia identifies a long-term source of returns with the potential for shorter periods of underperformance—these may be wonderful additions to traditional portfolios, but they are not arbitrage opportunities.

History shows that these periods of underperformance can last several years. They can feel even longer when you are in the middle of one.[22] Tough periods for factor investing, particularly in the wrong single factor, have included the value drawdowns of 2018–2020 and 1999–2000 (which included a junk rally in 1999), the momentum crash of 2009,[23] and the very brief, but sharp, crash of factors in August 2007. While these memories will be vivid for many, there are plenty of earlier examples as well. In fact, in the case of value, Mikhail Samonov has a blog post documenting its backtested performance over two centuries, with plenty of drawdowns along the way. Ilmanen et al. (2021) and Baltussen, Swinkels, and Van Vliet (2021) examine factor returns over a century and document periodic drawdowns among all factors.

In Exhibit 4, we examine the range and average of the rolling, three-year, realized Sharpe ratio of four factors (value, momentum, defensive, and carry) and multifactor portfolios of these four factors applied to five different asset classes (stocks and industries, equity indices, fixed income, currencies, and commodities) over the last century. As the chart demonstrates, each of these factors and multifactor portfolios, regardless of the asset class to which they were applied, experienced a meaningfully negative Sharpe ratio over some three-year period. Notably, these downside properties and long-term Sharpe ratio distributions are comparable with those of traditional markets, namely equities and bonds, as shown on the far right of the chart.

Exhibit 5 shows that even a "well-behaved," (i.e., normally distributed)[24] random variable with mean and volatility similar to those of the factors will experience significant drawdowns every once in a while. In fact, you would need a Sharpe ratio of at least 1.2 to drive the probability of a –30% or worse drawdown some time over 25 years down to less than 1%, as shown on Exhibit 6.

While even normally distributed returns can yield significant drawdowns, factor returns are less well behaved than a normal distribution. This is especially true over shorter intervals. Additionally, it is important to emphasize that there is significant time-variation in factor return properties. For instance, the correlation of factors and multifactor portfolios to traditional markets, though realizing near zero over the long-term, varies meaningfully from negative to positive over time.[25]

In addition to the investment horizon consideration, combining factors into a multifactor portfolio helps to mitigate tail events. For example, value and momentum individually applied to stock and industry selection have fat tails over short horizons,

[22] Some implementations of single factors have even gone through decade-long periods of anemic performance; for a single factor, that is not statistically shocking at all (and the same decade-long drought can occur for the market portfolio itself). But statistics aside, it can feel like an eternity.

[23] Over March to May 2009 in the sharp market turnaround following the global financial crisis, the momentum factor experienced a negative standard deviation event well in excess of conventional bounds. Value, however, delivered over the same period a meaningfully positive return that allowed a multifactor portfolio that combined the two factors to suffer a milder drawdown.

[24] And most investing/financial series are at least to some degree "fat-tailed" as compared with the normal distribution.

[25] The five-year rolling correlation of factors and multifactor portfolios across markets and asset classes to the broad equity market ranged roughly from –0.7 to +0.6 over the past century.

EXHIBIT 4

Range of Three-Year Rolling Sharpe Ratios across Factors and Asset Classes (July 1926–August 2022)

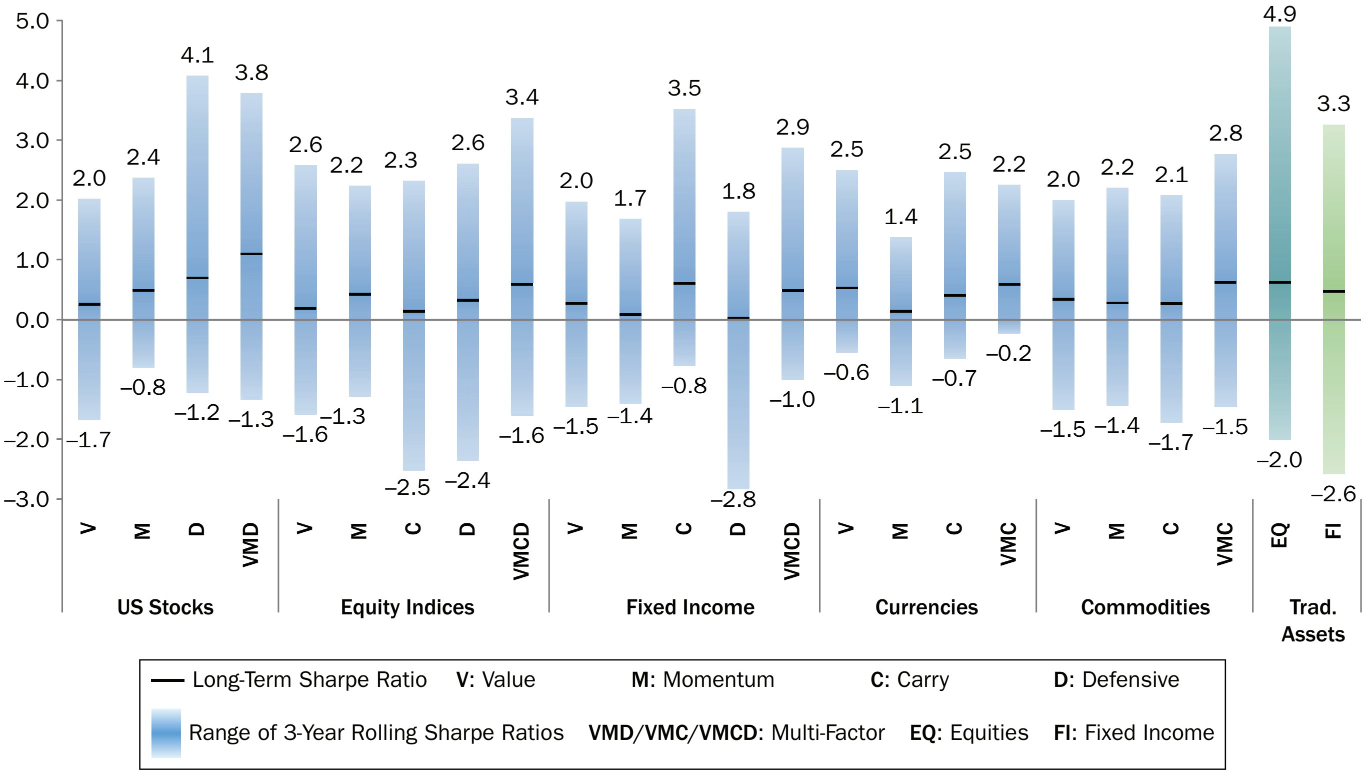
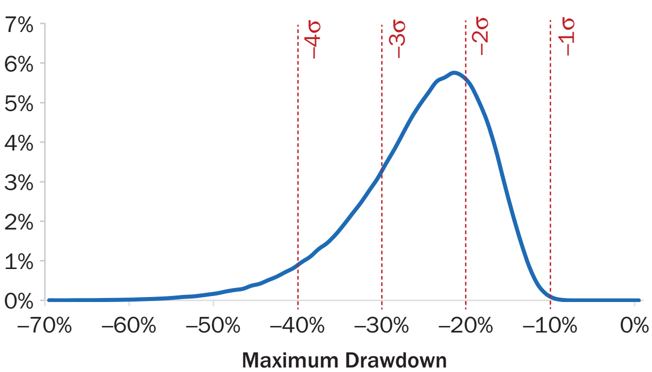


EXHIBIT 5

Probability Distribution of the Maximum Drawdown for Normally Distributed Variable with 10% Vol and 0.5 Sharpe Ratio over a 25-Year Window



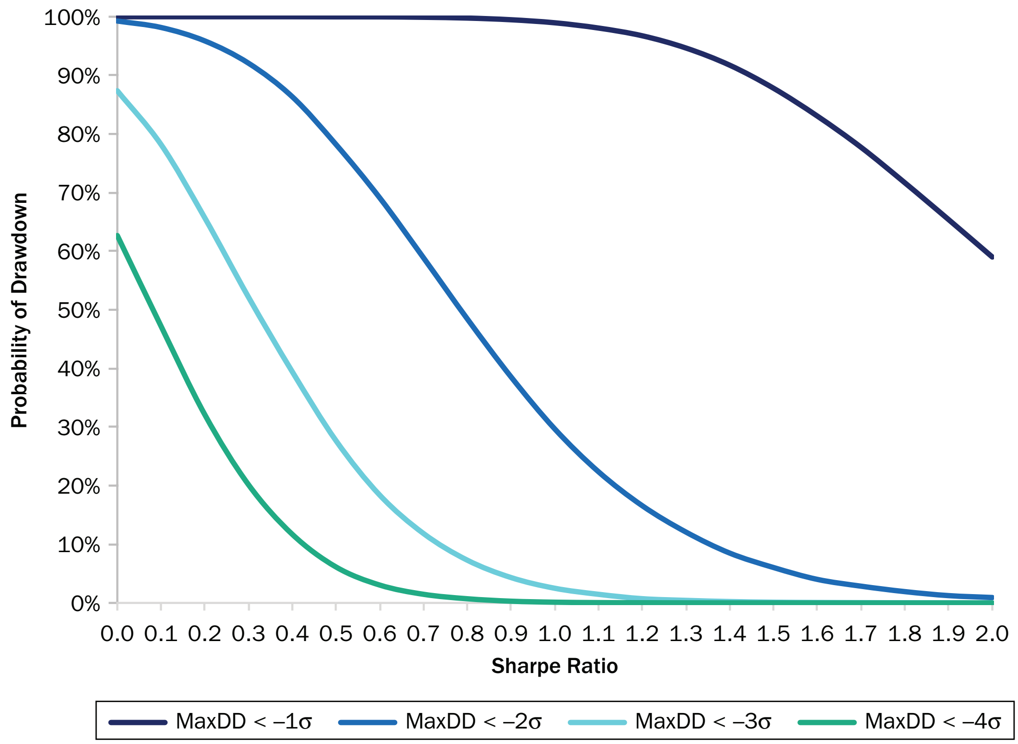
where value is positively skewed and momentum is negatively skewed. When combining value and momentum together, these tail properties lessen significantly and become comparable with other factors, including traditional markets. The momentum crash of 2009 is a good illustration of that. Over March to May 2009 in the sharp market turnaround following the Global Financial Crisis, momentum experienced a very meaningful negative standard deviation event, while an equally weighted combination of value and momentum saw a milder drawdown.[26]

While it is never easy to live through a multi-year performance drawdown, these tough periods are inherent to a factor investment strategy and may indeed be necessary to generate factor premia in equilibrium. They are probably part and parcel of any successful long-term investing strategy that can be run at institutional scale (quant and non-quant). As we will discuss, if factors were a free lunch—sure positive return with no risk—their premia would vanish quickly due to arbitrage activity.

[26] UMD experienced a –43% return from March to May 2009, while an equally weighted combination of UMD and HMLDEVIL experienced a –9% drawdown over the same period (Asness and Frazzini 2013).

EXHIBIT 6

Sensitivity of the Probability of Maximum Drawdown to the Sharpe Ratio (normally distributed variable with 10% volatility, σ, over a 25-year window)



#3. *Fiction*: Factor Diversification often Fails when You Need It the Most

A complaint, often misguided, voiced frequently during 2018–2020, is that factor diversification "often fails when you need it the most." There are two different versions of this claim. One version focuses on situations in which the factors "fail to diversify" each other, amidst terrible performance by one. The other version of this fiction is about times when factor investing "fails to diversify" bad market performance. We will address each of these in turn.

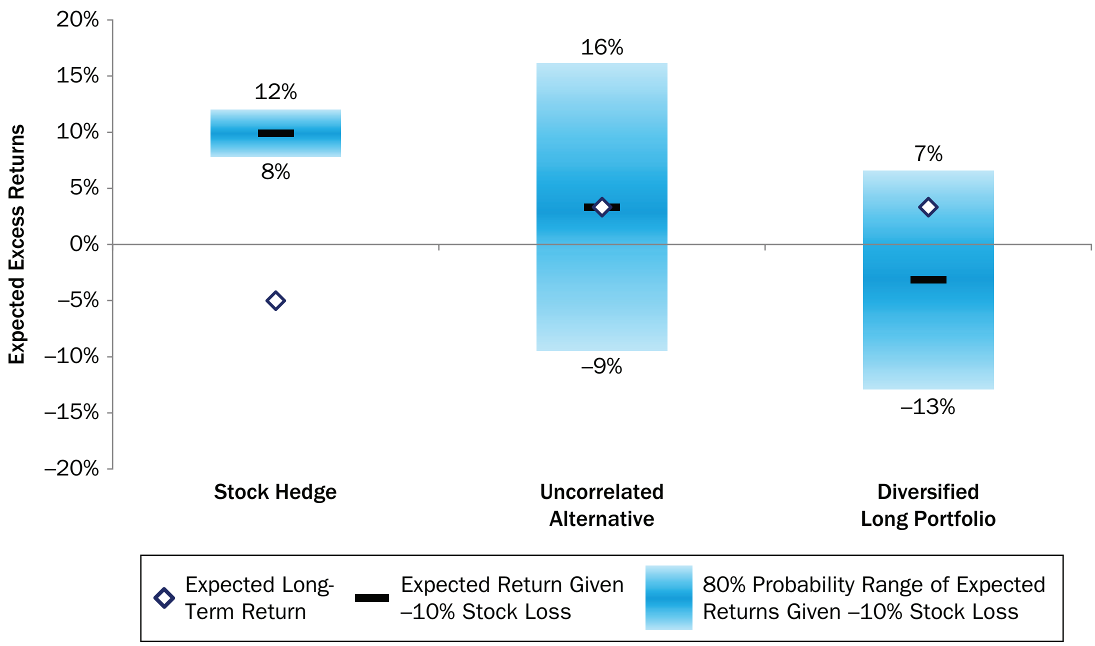
Two problems underly both versions of this fiction. The first problem is an excessive focus on the short term. Over short periods, the range of possible outcomes is larger (recall the fatter tails at shorter horizons we just covered), whereas longer term, one expects returns and correlations to converge to their expectations.[27] The second problem is mistaking diversification for a hedge. A hedge is an offsetting bet against risk that usually does not get rewarded long-term and often costs you something, (e.g., buying put options to protect against equity market downturns). In contrast, diversification merely requires that two return streams are not perfectly aligned (i.e., that their correlation is reasonably less than 1). This diversification can be very beneficial over time, but it does not make the diversifying asset a consistent hedge.

Let's start with the myth that factor investing "fails" to diversify the market when most needed. This fiction was a topic of much discussion during the Covid-induced equity market selloff in early 2020, when the world appeared to be falling apart, and market-neutral, multifactor investing simultaneously suffered (largely as the market decided, ex post wrongly, that Covid would spell the doom of value stocks).

[27] Asness, Israelov, and Liew (2011) covered this topic in an unrelated context.

EXHIBIT 7

Hypothetical Expected Outcomes when Stocks Are Down by 10% versus Cash



NOTE: See Mendelson and Mees (2019).

"Market neutral" neither implies nor requires "market offsetting" (a hedge). Of course, being market neutral merely indicates that performance will be unrelated to that of the market. Unrelated does not mean zero or the same return regardless of market movements. It means on average there is no pattern to factor returns associated with market returns. So, to state the obvious, a market-neutral strategy may perform positively or negatively regardless of what the market is doing (although to be useful it must be positive over the long-term average!). Historically, factors have done both well and poorly when the market is down, on average being close to a zero correlation. Indeed, while many market-neutral, multifactor strategies suffered during the market selloff of early 2020, these same strategies performed very well in early 2022 when the market slid. Conversely, they performed poorly during both the bull market of 1998–2000 and well during the bearish early 2000s.[28] At some point, a market-neutral strategy is bound to perform poorly when the market is cratering, as was the case in 2020. And, at other times, it will perform extremely well during market downturns. That is how diversification works. It is not immunization for short-term fluctuations, but a long-term risk-reducing effect.

While factor investing does not hedge the market, it can provide valuable diversification, as illustrated in Exhibit 7, which shows hypothetical expected outcomes of various arbitrary investment approaches in a significant down market. The stock market assumes a 5% excess long-term expected return with 15% annualized volatility. The "stock hedge" assumes to have a –0.99 correlation to the stock market with the same volatility and a –5% expected return. The "uncorrelated alternative" assumes zero correlation with the stock market, with annualized volatility of 10% and the same Sharpe ratio as the market (0.33). The "diversified long portfolio" (e.g., risk

[28] For further discussion on this topic, please refer to Blitz (2022), which documents that stock selection factors tend to perform well in decades when market premia are low (2000s and 2020s, to date) and less well in decades when market premia are high (1990s and 2010s).

EXHIBIT 8

Realized Return Correlations (July 1957–August 2022)

	HMLDEVIL	UMD	QMJ
HMLDEVIL	1.00	–0.65	–0.24
UMD		1.00	0.30
QMJ			1.00

parity portfolio) assumes a 0.65 correlation to the market with 10% volatility and the same Sharpe ratio of 0.33. Here, a market-neutral multifactor strategy would fit into the "uncorrelated alternative" category, with the numbers chosen to fit what those strategies reasonably look like on average.[29]

We see here that the hedge makes money in a very tight range in the market swoon. But the other two investments, while making money on average, have a much wider range of outcomes. Of course, the advantage of the other two is that unlike the hedge, they have a positive long-term expected return!

Having addressed the misconception about factors' not diversifying the market, let's now turn to the idea of factors "failing" to diversify each other when most needed. At its core, this idea boils down to a more plainly questionable statement: "Functional diversification precludes negative returns." The more veiled version of this fiction arose frequently in 2018–2020, when significantly negative value performance dominated many multifactor strategies.[30] These events led some investors to conclude that these factors could not have been very diversifying to each other. Of course, the idea that diversification and negative returns are inconsistent runs counter to factor investing being risky, which we discussed in fact #2.

To illustrate the point that diversification does not preclude temporary domination by one factor, we can look at the empirical properties of a multifactor stock selection investment strategy that combines academic versions of stock selection value (HMLDEVIL), momentum (UMD), and quality (QMJ) factors. As shown in Exhibit 8, these themes are clearly diversifying to each other, with low to negative correlations.

The phenomenon of one factor dominating the performance of a multifactor strategy is not unique to 2018–2020. Exhibit 9 shows there are many periods in which a single factor, although not always the same one, can dominate performance. Specifically, we graph the rolling three-year correlation between each of the themes and the multifactor strategy that combines them.[31] Not only are there short-lived periods in which the portfolio becomes highly correlated with each of the factors individually, but there are also subperiods in which some of these univariate correlations become negative. Correlations among factors change through time, which drives the variation we see in Exhibit 9. Such is the nature of having diversified sources of return.[32]

There are different ways of making the most of diversification among factors, including viewing diversification as an opportunity to take more meaningful risk in the standalone themes.[33] While greater risk taking in the factors underlying the portfolio

[29] It is important to note that we do not cover the trend factor in this article, also known as time-series momentum. As detailed in Moskowitz, Ooi, and Pedersen (2012) and Hurst, Ooi, and Pedersen (2017), trend exhibits tail-hedging properties, making it an ideal candidate to reduce downside risk in a diversified portfolio.

[30] It is worth noting the eight years prior to 2018: During this period, value generally disappointed, with some versions experiencing a protracted drawdown, but the other factors more than made up for it. Multifactor investing can help when one factor performs poorly over long periods.

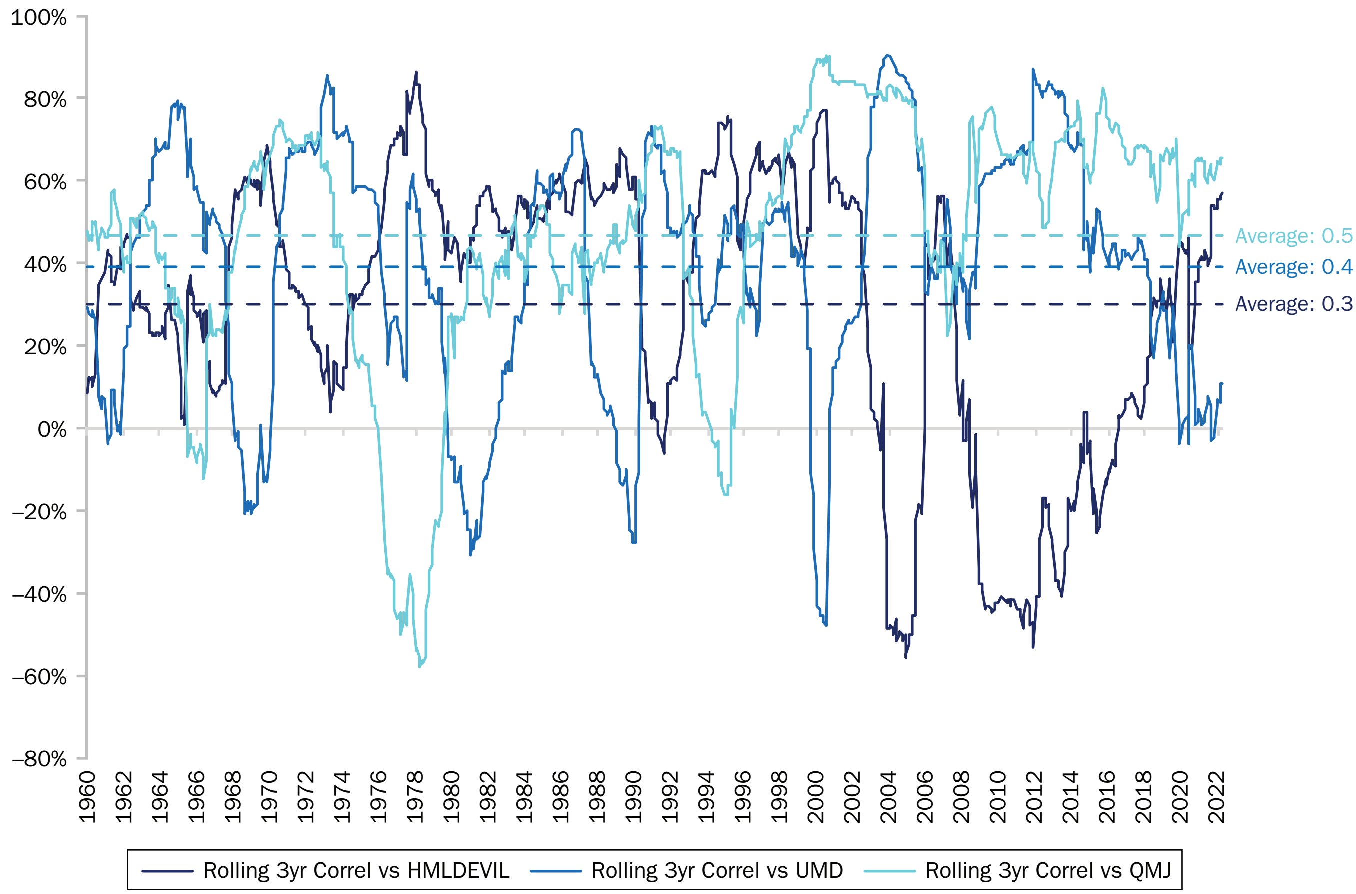
[31] Incidentally, at broadly equal risk weights. The strategy uses US factors and is rebalanced monthly.

[32] While not visible in Exhibit 9 as it is using monthly returns, the second week of August 2007, known as the "Quant Meltdown," saw a large and rapid deleveraging over the course of a few days. This led to very strong comovement across factors, hence to a significant spike in correlations (at high frequencies), which then quickly reversed.

[33] The flipside of long–short multifactor, multi-asset diversification meaningfully reducing portfolio volatility is that greater leverage is needed to achieve a given volatility target. The shorting and leverage requirements may explain why the long-only applications (smart-beta portfolios) are in practice more common ways of factor investing than the purer and more effective long–short applications (alternative risk premia portfolios).

EXHIBIT 9

Rolling Three-Year Correlation between a Multifactor Stock Selection Portfolio and Its Underlying Factors (July 1957–August 2022)



may be beneficial to performance in the long term, over shorter periods, it can of course translate into larger magnitude losses from a single factor. Ironically, such an outcome could sow doubt in a multifactor strategy's diversification—"How can this process be diversified if it lost so much at the hands of one factor?" The bottom line is that while individual factors can dominate over the short term, longer-term performance tends to be driven by more balanced gains across all of the factors.

It is worth noting that the flip side of this gripe about factors "failing" to diversify each other is when factors diversify each other "too much," so much so that a multifactor portfolio becomes identical to the market (or cash). This misconception goes back to the confusion of diversification for a perfect hedge. As already shown in Exhibit 9, none of the pairs of themes are perfectly negatively correlated or anywhere close to it. Even value and growth, often regarded as "opposites," are not diametrically opposed (unless postulated so by defining growth as the opposite of value—something that is not necessary or even particularly helpful). In fact, growth-related factors including relatively short-term changes in earnings and margins tend to be quite complementary to value. Adding growth to value may help eliminate value traps, and likewise adding value to growth yields a GARP strategy (growth at a reasonable price).

Big picture, diversification is valuable, but no one should ever claim it can entirely eliminate losses.[34] Diversification doesn't fail any more often when "most needed"

[34] In fact, as we already discussed, elimination of losses yields a free lunch that ensures no long-term premium remains.

versus other normal times. However, when diversification does not prevent one bad apple from spoiling the bunch, it certainly *feels worse* than when positive performance aligns.

#4. *Fact*: Factors Work across Many Markets and Conditions

We mentioned in fiction #1 that one of the best ways to combat data mining concerns is to find robust out-of-sample evidence. For the main factors academics and practitioners focus on, and which we highlight in this article, there is a ton of out-of-sample evidence supporting their efficacy. Some of that evidence consists of applying factor themes to other markets and asset classes, which we focus on here.

The original studies for value, momentum, and defensive/quality focus on US individual stocks,[35] and the original studies on carry strategies apply them to developed market currencies.[36] However, there is ample evidence that these factor themes apply easily and effectively to many other markets, other asset classes, and on subsets of assets within a market. For example, within the US equity market, significant factor premia exist among small-, mid-, and large-cap stocks separately (Fama and French 1992; Hong, Lim, and Stein 2000; Grinblatt and Moskowitz 2004; Hou, Xue, and Zhang 2015; Novy-Marx 2013; Israel and Moskowitz 2013). Factors also produce abnormal returns both across and within industries (Asness, Porter, and Stevens 2000; Moskowitz and Grinblatt 1999; Grundy and Martin 2001; Cohen and Polk 1998) and deliver premia among both low and high volatility stocks (Zhang 2006; Stambaugh and Yuan 2017). While the magnitude of the return premia can vary among subsets of stocks, typically being bigger for smaller and higher volatility securities, their existence is robust across all of these segments.[37]

In addition, factor premia appear to be robust in international equity markets, for both developed and emerging markets (Rouwenhorst 1998, 1999; Griffin, Ji, and Martin 2003; Asness, Moskowitz, and Pedersen 2013; Fama and French 2012; Frazzini and Pedersen 2013). The magnitudes of the premia are roughly the same across markets and tend to move up and down together (Asness, Moskowitz, and Pedersen 2013).

Factors have also been applied to other asset classes, including equity index futures, government bonds, corporate bonds, commodities, currencies, options, and even sports betting contracts (Gorton, Hayashi, and Rouwenhorst 2013; Asness, Moskowitz, and Pedersen 2013, 2015; Bhojraj and Swaminathan 2005; Frazzini and Pedersen 2013; Koijen et al. 2018; Brooks and Moskowitz 2018; Baltussen, Swinkels, and Van Vliet 2021; Ilmanen et al. 2021; and Moskowitz 2021). The evidence overwhelmingly supports the idea that factor investing works equally well in many markets and asset classes. This evidence, coupled with the out-of-sample evidence through time, indicates that factor premia are robust and reliable sources of returns that pervade all markets and asset classes.

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[35] For value, see Statman (1980), Rosenberg, Reid, and Lanstein (1985), and Fama and French (1992); for momentum, see Jegadeesh and Titman (1993) and Asness (1994); and for quality/defensive, see Sloan (1996), Piotroski (2000), Ang et al. (2006), Novy-Marx (2013), and Frazzini and Pedersen (2013).

[36] See Meese and Rogoff (1983) and Fama (1984).

[37] The evidence on factor efficacy within versus across industries is interesting, where accounting-based signals such as value and profitability are typically stronger within an industry, due to differing accounting practices across industries (Asness, Porter, and Stevens 2000; Cohen and Polk 1998), but price-based measures such as momentum seem to work at least as well, if not better, across industries (Moskowitz and Grinblatt 1999), perhaps because price momentum is inherently comparable across very different companies while accounting measures may have more of an "apples to oranges" component.

While factor premia remain long-term robust phenomena across markets, however, we also know they can experience significant variation in performance. The empirical finance literature provides substantial evidence of time variation in factor risk-adjusted returns. Using a century's worth of data, Ilmanen et al. (2021) test formally for variation in factors' Sharpe ratios over time and find significant variation beyond just random chance. A deeper question is whether this variation can be explained or predicted (the latter we address later in this article). An important question we address here is whether this variation is related to market conditions and macroeconomic environments.

Examining factor performance in different market environments serves dual purposes. First, it is useful to understand when factors may or may not work well both from a practical perspective—what type of market environments favor or disfavor factor investing?—as well as from a robustness perspective—how reliable are the premia to market conditions? Second, examining how factor performance varies with the macroeconomy serves as a useful test for many theories seeking to explain why factor premia exist.

Recall the economic intuition behind factor premia (introduced and discussed in fiction #1): The premia are compensation for bearing risk or from exploiting a behavioral anomaly. If factors are partly compensation for risk, their returns should vary as a function of the level of risk perceived by the market and the market's tolerance for that risk. If that risk changes over time due to macroeconomic conditions, then these strategies will be sensitive to the macroeconomy. For instance, part of the carry premium may be compensation for exposure that generates large losses during extreme times of heightened risk aversion.[38] If extreme times are related to or driven by macroeconomic conditions and times of limited capital such as funding squeezes, then we might gain a better understanding of what drives these premia by further studying the macroeconomy. Furthermore, if we can forecast these macroeconomic episodes, then there may be scope for tactical trading or timing of the factors, an issue we take up in fact #8.

If factors are partly driven by behavioral phenomena, their returns can vary due to sentiment in the market or shifts in mispricing. Sentiment and mispricing can also be related to the macroeconomy. For instance, value strategies that exploit the discrepancy between relatively undervalued and overvalued assets may go through periods of lower risk-adjusted returns caused by irrational expectations/exuberance. The exuberance could be fueled by the broader economy, where growth expectations are excessive or investors extrapolate recent macro news too aggressively, or perhaps exceptionally accommodative central bank policy, for example.

While theory suggests there could be a link between the macroeconomy and factor returns, this question is ultimately an empirical one. Exhibit 10 plots the Sharpe ratio of factor portfolios, using the century of data series obtained from Ilmanen et al. (2021), across different economic environments. We focus on economic growth, inflation, and real interest rates as the chief economic drivers of traditional markets. We also condition on the volatility of the market, which may be a proxy for risk management, funding constraints, and market liquidity. We follow the approach of Ilmanen, Maloney, and Ross (2014) to construct each of these macroeconomic indicators.

As fits basic intuition, we find meaningful sensitivity of traditional equity and bond markets to these macroeconomic variables with large and significant *t*-statistics. However, there is little evidence that time variation in factor premia is related to macroeconomic environments, with Sharpe ratios of the factors being largely stable across different economic regimes (growth vs. decline, high or low rates, high or low

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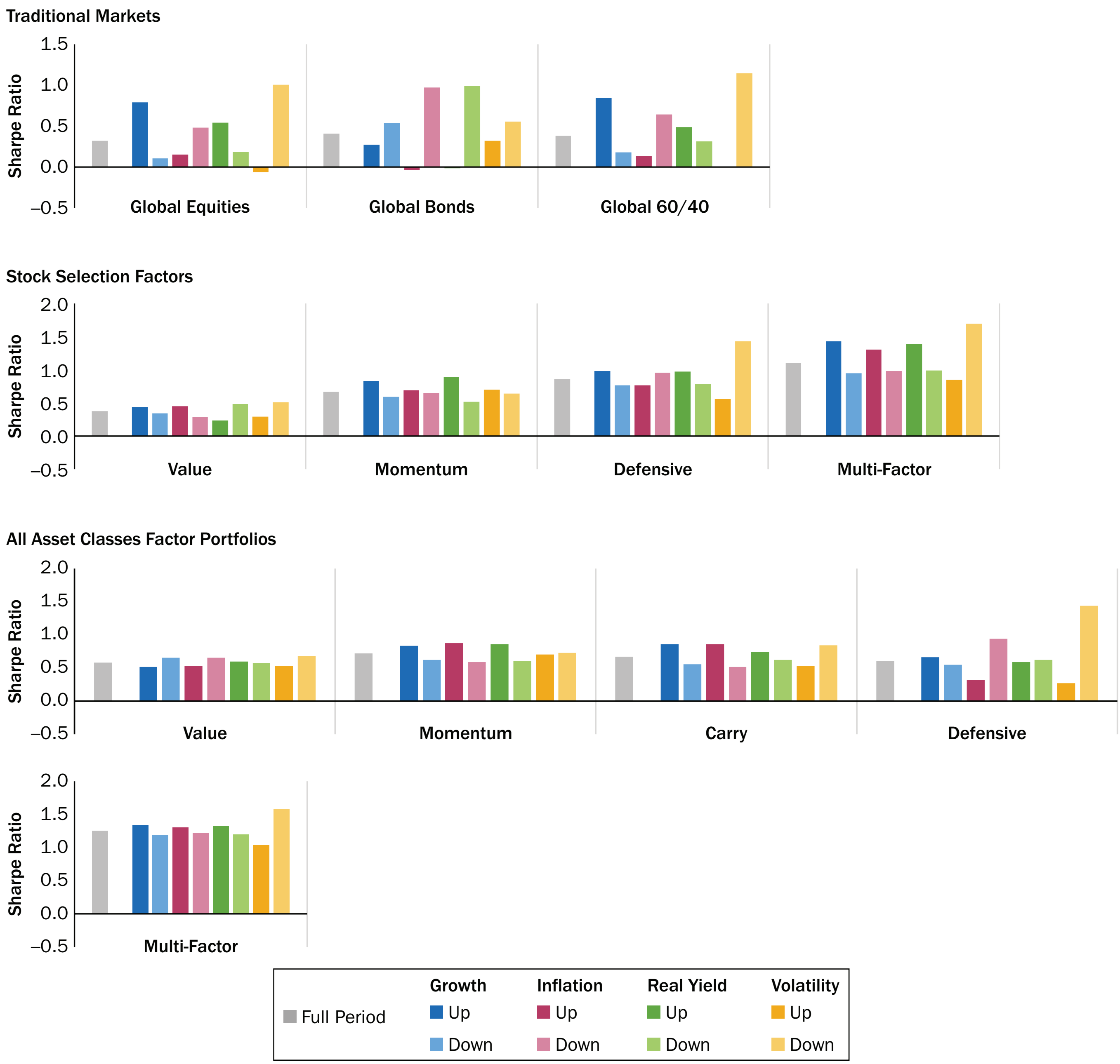
[38] This is especially true for currency carry and volatility carry strategies (see Brunnermeier, Nagel, and Pedersen 2008).

EXHIBIT 10

Performance across Growth and Inflation Environments (January 1972–December 2021)



volatility, etc.). This does not mean factors perform ex post well in every environment just that they do so on average. There is no reliable significance in factors' exposure to the macroeconomy, with the possible exception of the defensive factor being sensitive to inflation and volatility.

At the multifactor portfolio level, which diversifies across the factors, the impact of economic regimes is even more muted, suggesting some of the variation in factor returns is diversifiable.

Ilmanen et al. (2021) and Ilmanen, Maloney, and Ross (2014) also examine factor sensitivity to macro variables and find very similar results. Ilmanen et al. (2021)

EXHIBIT 11

Sensitivity of Low-Risk Factors to Interest Rates (February 1976–March 2022)

	BAB Dollar Neutral	BAB Beta Neutral	BAB Beta and Industry Neutral
Bond Beta	0.45	0.29	–0.01
	(4.66)	**(2.93)**	(–0.18)
Equity Beta	–0.78	–0.13	–0.01
	(–23.14)	**(–3.75)**	(–0.33)
Annualized Alpha	7.4%	10.4%	9.7%
	(4.01)	(5.46)	(6.13)
Adjusted R^2	49%	3%	0%

examine variables related to the business cycle, growth, monetary policy, political uncertainty (Baker, Bloom, and Davis 2016; Caldara and Lacoviello 2018), volatility risk, downside risk, tail risk, crash risk (Brunnermeier, Nagel, and Pedersen 2008; Lettau et al. 2014; Jiang and Kelly 2014), liquidity risk (Pastor and Stambaugh 2003; Acharya and Pedersen 2005), and investor sentiment (Baker and Wurgler 2006). They fail to find any reliable evidence of factor performance sensitivity to these variables using a century of data.

The bottom line is that factors work similarly across many economic environments and conditions. This is great news from a diversification perspective, as it provides a source of returns whose fortunes differ from those from traditional asset classes such as the stock and bond market. When the macroeconomy changes, we can expect stock and bond markets to be affected, but not factors, which (on average) perform steadily through these periods. As discussed previously, however, this also has a downside—when factors themselves experience tough times, it will not likely be tied to the macroeconomy and therefore defies an easy economic story and does not give investors an obvious catalyst to root for to spur recovery. This is the downside of diversification—sacrificing intuition and narratives over short periods for better long-term risk–return profiles. In turn, a lack of narratives over short periods can make factors harder to stick with when tough times hit as there is no “easy story.” Good things don’t come for free!

The results we present pertain to academic factors formed from published papers. However, it is important to recognize that there is not a single or best way of building any factor-based strategy. When designing a strategy, managers and practitioners are faced with multiple choices and these can have a meaningful impact on the factor’s sensitivity to macroeconomic environments. Consider a stock selection strategy that goes long stocks with low market beta and short stocks with higher market beta (“betting-against-beta” or BAB). This strategy would have drastically different properties depending on its weighting scheme. For example, in Exhibit 11, “BAB Dollar Neutral” weights stocks in a dollar-neutral way, which results in a net negative beta and significant exposure to both equity and bond markets. In contrast, “BAB Beta Neutral” weights the portfolio in a market-neutral way by taking more dollar exposure to the longs than the shorts to achieve a net beta of zero, rather net dollar exposure of zero. The resulting portfolio has a meager exposure to equity and bond markets as a result.[39]

Beside weighting schemes, there are many other design choices, such as the metric used to compare assets, what risks are controlled for, liquidity constraints, etc. In the table below in Exhibit 11, we include a ‘BAB Beta and Industry Neutral’ portfolio that neutralizes industry exposure in addition to being market neutral. For this portfolio, the equity and bond market betas become small and insignificant with minimal impact on the strategy’s alpha and *t*-statistic. Hedging out industry exposure can

[39] Fixed income strategies provide another example of how design choices matter for macro sensitivity. Consider a bond factor that takes relative value positions in bonds (or bond futures). The manner in which bonds are weighted, whether notional, duration, volatility or beta, would have a dramatic impact on the factor’s behavior across different interest rate and growth regimes. For instance, a portfolio that is long (overweight) US Treasuries and short (underweight) Japanese government bonds is not market neutral given the large volatility difference between the two markets. For quite some time (though perhaps not forever going forward), when 10-year US Treasury yields move by 1 basis point, 10-year Japanese government bonds yields are more likely to move by 0.5 basis points. Hence, a notional or duration weighting would be prone to creating large “unintended” exposure to global bond markets.

further reduce a factor's sensitivity to the macroeconomy, and other design choices can increase or decrease that sensitivity, too.

The bottom line is that factor strategies in general are not very sensitive to macroeconomic environments, but seemingly small design choices that many quantitative managers use to enhance their factor portfolios can reduce these macroeconomic exposures further to a negligible level (again, that does not mean they always win, just that when they win or lose is not very macro sensitive).

#5. *Fiction*: Factors Do Not Work Anymore in the New Economy

How many times have we heard the pronouncement "This time, it's different"? We will call it "TTID" for short. TTID claims arise most frequently when something that usually works is not working for a sustained period of time. Skeptics and Monday morning quarterbacks trot out all sorts of hypotheses to explain why an old idea is now dead. The claim a "New Economy" renders factor investing—actually not just factor investing but active traditional stock picking based on rational factors—dead has been declared more than once—recently in 2018–2020 as well as during the Tech Bubble of the late 1990s. In the case of factor investing, we believe the TTID mindset tends to underestimate the robustness of factors to different environments.

For starters, there have been many extraordinarily transformative changes over the last couple of centuries: railroads, steamships, the Industrial Revolution, the Great Depression, World War II, the Cold War, space exploration, stagflation, Reaganomics, personal computing, the internet, and social media, to name just a few. And yet we have seen factors continue to work, despite these ongoing changes—even the ones occurring in the last few decades. This persistent long-term success should come as no surprise, given the risk-based and behavioral explanations for the factors are invariant to old versus new economy conditions. As the world has progressed, compensation for risk did not become unnecessary and investors have not magically become perfectly rational.

Take, for example, the value factor. It is a misconception (as one can see from its long-term success through decades and indeed centuries of radical change) that it cannot handle technological change. Investors are often well aware of technological change. If value works because of behavioral reasons, it is because investors overextrapolate whether or not change occurs (and in some cases, change can actually contribute to overextrapolation). One day perhaps this tendency will go away, but we wouldn't hold our breath!

One specific version of TTID is that accounting information is no longer relevant in the new economy. Again, this is not the first time for even this specific theory. During the Tech Bubble, some claimed the number of "double clicks" were more important than a company's earnings. In their article "Is (Systematic) Value Investing Dead?" in a subsection entitled "Do Fundamentals Still Matter for Stock Returns," Israel, Laursen, and Richardson (2021) conduct a simple test to establish that fundamentals do indeed still matter. Specifically, they simulate a simple value strategy with perfect foresight of future earnings. Unsurprisingly, the resulting Sharpe ratio is quite high over the long run, including following the Tech Bubble (it turns out knowing the future helps). Similarly, they demonstrate that contemporaneous changes in earnings expectations usually explain a significant portion of stock return variance. But they also document that the 2018–2020 period and the Tech Bubble have been outliers with respect to these relationships where fundamental did matter less. Simply put, fundamentals can stop "mattering" over short periods like the aforementioned ones, but they tend to matter most of the time and over the long run and (not surprisingly) continue to matter in 2021–2022.

While we believe in factors' robustness, we equally espouse innovation. The field continues to advance, constantly searching for better ways to measure the same concepts and also recognizing that some specific and more basic metrics may see their efficacy degrade over time. Accordingly, a commitment to innovation is important. Over the last two decades, we have published some of our ideas regarding improvements over the academic measures of factors. These ideas have included using diversifying metrics to capture an investment theme,[40] making adjustments for country and industry membership before using raw data for stock selection, and applying these broad ideas to other asset classes beyond stocks. Current and future enhancements will be driven by a combination of novel data sets (including those sourced in-house) and novel ways of processing old information, including but not limited to machine learning techniques. Importantly, like diversification, innovation will not always save you from poor performance, rather, again like diversification, its goal is to improve long-term outcomes.[41]

#6. *Fact*: Factors Were Not and Are Not Too Crowded, Despite Being Well Known

How can factors not be too crowded if everyone knows about them?[42] We covered this a bit in *fiction* #1. Many of the best economic explanations for why factor premia exist rely on a set of investors willing to take the oher side of factor investing. Under these explanations, investors are aware of factor premia, but choose not to invest in them because they either do not like the risks associated with factors or the characteristics of those factors from a behavioral standpoint. This dynamic allows factor premia to be sustainable in equilibrium and never be "too crowded" or arbitraged away. This story is different than pure, idiosyncratic alpha coming from say mispricing or new information. Riskless alpha is something all investors would want, and therefore it would be competed away quickly. In other words, there is no long-run sustainable other side to riskless alpha strategies, and should it exist, it would be susceptible to being arbitraged away (crowded out) quickly (although nice while they exist!).

Of course, even under risk-based or behavioral explanations for factors that give a rationale for who is on the other side, demand to take either side of factor bets can vary over time as tastes for risks and preferences change. If everyone decided to be invested in factors and no one was willing to take the other side—an improbable scenario where everyone's risk appetite and/or preferences are aligned in the same direction—factor premia would certainly disappear. More realistically, there are times when factor investing may appear "more crowded" if fewer investors are willing to take the other side, relative to those wanting to invest in factors. The reverse can be true, too, where there are more people willing to bet against factors than for them. This ebb and flow of demand for and against factors should show up in prices and valuation ratios and hence future expected returns. Thus, one way to gauge the "crowdedness" of factors is to look at valuations, such as value spreads—defined as

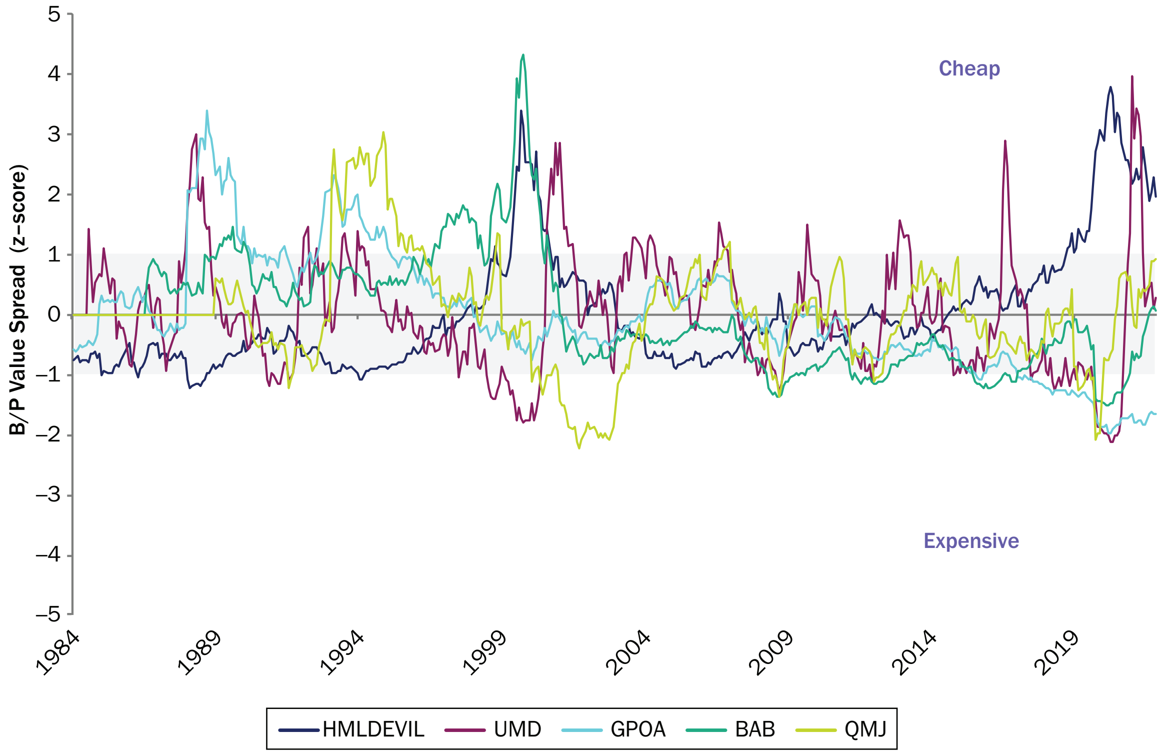
[40] In the case of momentum investing, we have advocated using versions of momentum based on growth in fundamentals alongside price momentum. There are many other innovations that do not get published for fear of being competed away.

[41] For example, Israel, Laursen, Richardson (2021) also show that, while there is some merit to the rise of intangibles becoming increasingly important, value adjusted for intangibles experiences a drawdown in parallel with more basic versions of value—ruining a favorite story of many that value died in 2018–2020 because it ignored this information.

[42] We subcontracted this section to Yogi Berra (the editor's all-time favorite baseball player: three time Most Valuable Player who led the New York Yankees to 10 World Series Championships.)

EXHIBIT 12

Stock Selection Factors—Value Spreads (June 1984–April 2022)



the discrepancy between the average book-to-price ratio of the long side of a factor relative to the short side of a factor.[43]

Some stories for the recent underperformance of factors have followed this logic, claiming that the increasing commoditization and popularity of factor investing led to a decrease in return expectations that manifested over the 2018–2020 period. However, such decay in factor efficacy, if due to overcrowding, would look more like a slow decay to zero rather than an abrupt and sharp downturn into negative returns territory. This common story, that factors got too crowded leading to the 2018–2020 pain, is in fact backwards. They were not overcrowded—they were shorted!

Furthermore, valuation ratios of various factors do not support this type of story. Exhibit 12 plots the time series of valuation spreads of value (HMLDEVIL), momentum (UMD), profitability (GPOA), defensive (BAB), and quality (QMJ) factors. The value spreads indicate whether a factor looks "cheap" or "expensive" relative to its history, which is one indication of crowding into or out of a factor. Comparing the time series of value spreads across the factors suggests that crowding was unlikely to blame for the poor performance from 2018 to 2020. For example, the value factor was relatively cheap prior to 2018, having followed a decade of relatively lower performance, which indicated lack of crowding into the value factor. Yet, it was precisely the value factor that experienced the worst drawdown from 2018 to 2020. Conversely, the defensive factor looked relatively expensive and hence possibly crowded, yet it did very well during the subsequent 2018–2020 period.[44] These patterns are the opposite of what one would expect from a crowding story.

[43] We remind the reader that in other work we use far more diversified measures of valuation often, unlike the HML we use here, attempting to remove the industry or sector bet.

[44] Please refer to Ilmanen, Nielsen, and Chandra (2015) for further discussion on value spreads for the defensive factor.

Valuation-based crowding measures make sense for strategies with low turnover and predictable holdings but not for higher turnover strategies, such as momentum. There are other measures of crowding besides value spreads, too. When a trade becomes crowded, it usually causes an increase in price impact and trading costs, as more dollars crowd into the trade in the same direction. That price pressure can also exert excess correlation among stocks with similar style characteristics and excess volatility of those stocks, too. There is no evidence that trading costs, excess correlations among stocks, or excess volatility increased prior to the drawdown period in a manner consistent with crowding into these factors.

For a strategy to become crowded requires significant net inflows, which we can directly examine. Despite all of the press about factor investing and smart-beta strategies in the post-Global Financial Crises era, relatively modest flows went into factor-based strategies according to the data, as Lettau, Ludvigson, and Manoel (2018) show in their paper, "Characteristics of Mutual Fund Portfolios: Where Are the Value Funds?" This may seem surprising given the rapid growth in smart-beta strategies, many based on academic factors, over the last decade. Importantly, the largest group of such strategies are smart-beta, long-only funds whose exposure is dominated by market equity beta, often with very small exposure to the factors themselves.

Alquist, Jiang, and Moskowitz (2019) examine crowding in stocks generally, including an application to factors. They examine measures of flows from institutions, short positions, value spreads, abnormal trading costs, excess correlation, and excess volatility to capture crowding.

The main conclusions from this research are that crowding measures are not reliably predictive of alpha/expected returns or trading costs but may provide some indication that tail events are more probable or more extreme should a deleveraging event occur. These findings are intuitive in that a deleveraging event will impact crowded positions more as everyone tries to run for the exit at the same time. The lack of predictability for crowding on expected returns is consistent with there being a long-term set of investors willing to take the other side of factors. In the short term, extreme events might get exacerbated due to crowding, but the long-term efficacy of factor investing is largely unaffected.

Once a strategy is "discovered" and becomes well known, it can and will continue to work going forward as long as the other side of the trade does not disappear and as long as it does not become crowded. In this way, factor investing does not get arbitraged away.[45] This argument also extends to the equity premium and illiquidity premium we find in markets. Those, too, likely will not get arbitraged away because there remains a natural set of investors willing to take the other side of those bets (e.g., those who do not want equity risk or do not require liquidity). That does not mean these premia won't fluctuate over time, but a long-term positive premium is expected.

#7. *Fiction*: Everyone Should Invest in Factors

At this point this article might have already beat this one to death, but let's pile on anyway. Like stopping the killer in a horror movie, it probably takes several death blows, and yet he (and this fiction) may still come back.

Everyone can't invest in factors. Period. Factor investing, by definition, deviates from market weights and because everything adds up to market weights, if everyone invested in factors (with no one willing to take the other side), then prices would change until they matched market weights and the premium would disappear. This is

[45] See Asness (2015) for some examples, where both the risk-based and behavioral explanations we espoused earlier provide the rationale for a willing and sustainable other side.

precisely why the existence of a factor premium requires someone willing to take the other side.

With this in mind, it is also instructive to consider that those who do invest in these factors should understand *why* they are investing in them and the risks they bear. For example, factor premia are *not* a free lunch. They do not offer a riskless source of abnormal returns. Rather, they offer compensation for bearing additional risk or unpopular characteristics associated with it. That is, there must be a reason some investors do not want to invest in these factors, and any factor investor must understand and embrace that reason. If it's risk, then know that you are embracing and exposed to that risk. If it's a behavioral preference, then know that you are investing in things that other investors find unappealing.

Knowing why you invested in a factor in the first place is important for sticking with your investment decision. As we have shown, factor premia are reliable over long periods of time, so in order to reap the rewards from factor investing, an investor must be willing to stick with it, even during the dark times. Understanding why a factor delivers above-market returns helps in sticking with it through those tough times. And the key to successful factor investing is being able to stick with it in the long run. Not every investor can or should.

#8. *Fact*: Factor Discipline Generally Trumps Timing, Tinkering, and Trading

One of the most hotly debated topics in recent years among factor investing practitioners is the efficacy of factor timing.[46] Both academic research and our own internal research trying to incorporate factor timing into our strategies show that adding value to a well-diversified multifactor portfolio via factor timing is extremely challenging.

Before delving into the main topic of factor timing, a brief detour of market timing is instructive. Many charts, articles, and papers laud the cyclically adjusted price–earnings (CAPE) ratio, defined as price divided by the average of 10 years of earnings and adjusted for inflation, as a useful predictor of subsequent 10-year equity market returns. Despite the press, however, trying to time equity markets using the CAPE ratio in practice results in disappointing returns that are no better than a simple buy-and-hold approach.[47] If market timing is quite difficult, it stands to reason that factor timing is likely even harder because factors are more dynamic. While the market's composition will be largely the same six months from now, a factor's composition will change due to active rebalancing. Such active rebalancing can cause a factor's value spread to change in potentially unpredictable ways, even in the absence of moves in prices.[48]

Asness et al. (2017) investigate value timing of factor portfolios. In the context of a well-diversified multifactor portfolio that already includes value, the authors find little added benefit to implementing tactical value timing. Attempting to do so results in a larger bet on value than intended and weakens performance due to forgone diversification across the other factors. Exhibit 13 illustrates the point, emphasizing that value timing implemented within a multifactor portfolio looks a lot like static value investing and may detract from the benefit of strategic diversification.[49] Accounting for

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[46] See Arnott, Beck, and Kalesnik (2016a,b,c), Asness (2016a,b), Arnott, Beck, and Kalesnik (2017), Asness (March 2017a,b,c), Asness et al. (2017), and Asness (2019).

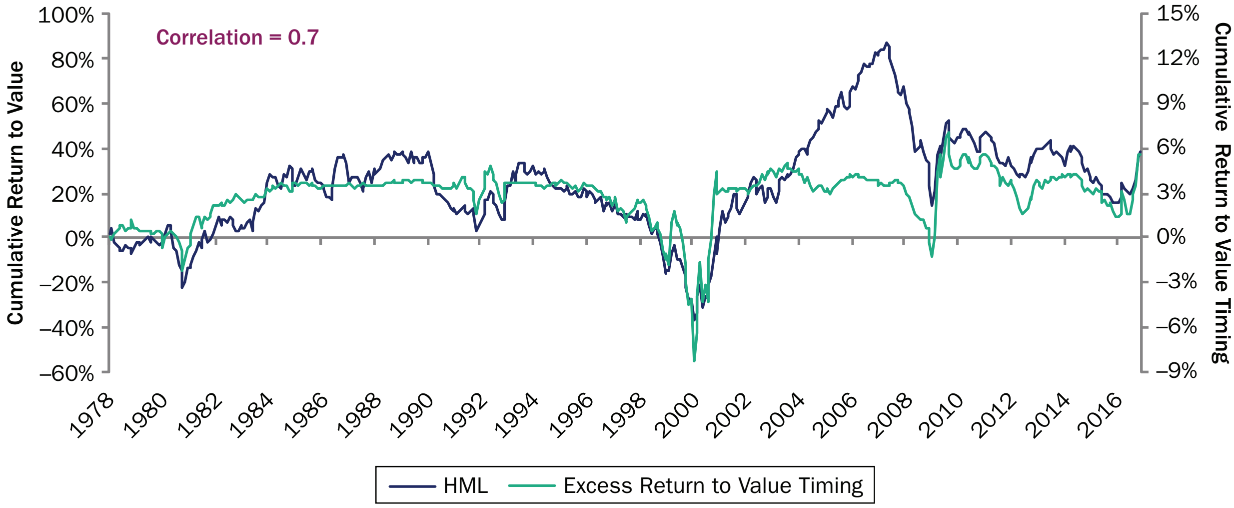
[47] This apparent puzzle is well covered and addressed in Asness, Ilmanen, and Maloney (2017).

[48] The value spread of a factor is the ratio of a measure of the average value, for example, book-to-price ratio, of the long side of a factor to the short side of the factor portfolio. It was introduced in Asness et al. (2000).

[49] We believe the correlation of 0.7 is somewhat understated as the total strategy risk is not varied that is, to keep leverage constant the strategy can be overweight expensive styles if other styles are even more expensive. If strategy risk is allowed to vary as in Asness (2016a), the correlation increases to 0.8.

EXHIBIT 13

Stock Selection Value versus Value Timing of Multifactor Stock Selection Portfolio (US Large Cap Equities, January 1978–December 2016)



the additional turnover and transaction costs associated with tactical timing results in further reduced performance net of costs (Ilmanen et al. 2021).

Despite these cautions on tactical timing, when the opportunity becomes attractive enough, it may warrant action—although there is no guarantee of near-term success. In fact, we have written about implementing a tilt toward the value factor in recent years,[50] when the factor was (and still is as we write this piece) extremely cheap. Its value spreads reached levels wider than the Tech Bubble peak (illustrated in Exhibit 14),[51] reflecting a historic disconnect between prices and fundamentals. Based on these value spreads, an initial tilt in late 2019 proved to be too early and was punished as value continued its slide in 2020. Eventually, however, in 2021 and 2022, value's performance started to turn around and a small tactical tilt delivered positive returns. This experience is a reminder that factor timing is difficult and you can never get it perfectly right, but it may be worthwhile in the long run, particularly in extreme situations such as the historic dislocations recently experienced.

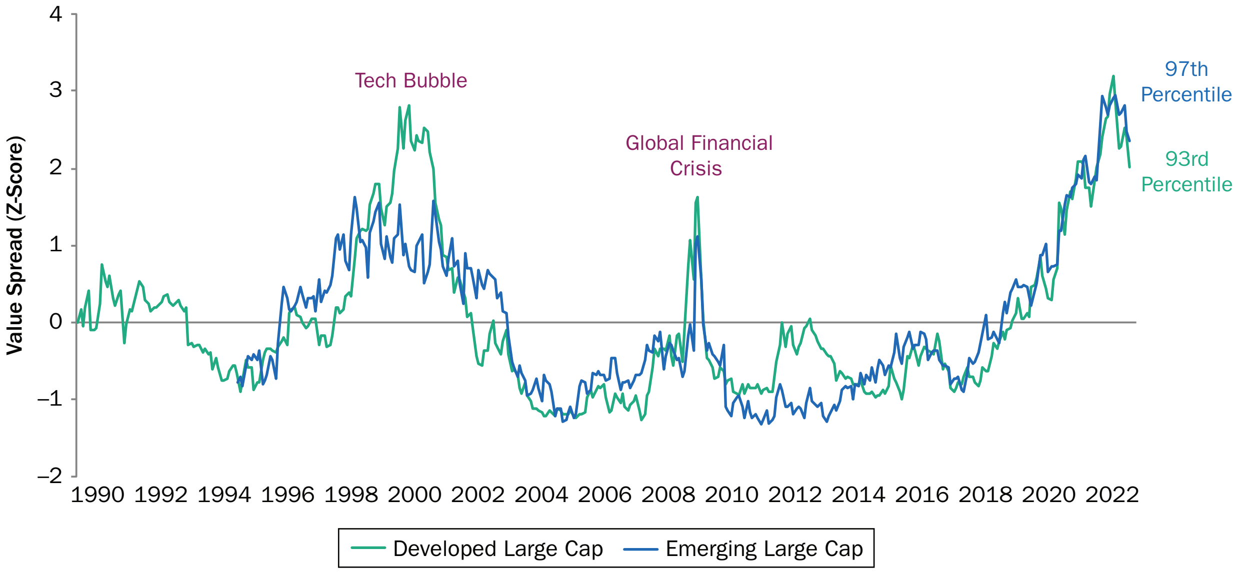
Besides value timing, other commonly used methods for factor timing include factor momentum (Gupta and Kelly 2019) and macroeconomic timing. Using a century's worth of data, Ilmanen et al. (2021) study these as well as a host of other timing signals and find that the performance additivity of factor timing is modest at best, with value spreads, factor momentum, and volatility timing providing the most positive results. As for factor timing using macroeconomic predictors, there is little evidence supporting it. Moreover, successful macroeconomic-based factor timing requires being "right twice": 1) being correct in predicting the macro environment and 2) forecasting factors' exposures to macro conditions, which, as shown previously in fact #4, are weak to nonexistent in most implementations.

[50] See Asness (2019).

[51] Note that in contrast to Exhibit 12, which computes book-to-price value spreads for the HMLDEVIL factor, Exhibit 14 measures spreads using five value measures (book-to-price ratio, earnings-to-price ratio, forecast earnings-to-price ratio, sales-to-enterprise value ratio, and cash flow-to-enterprise value ratio) and for an industry-neutral and dollar-neutral value composite constructed from the same five value measures. Spreads are measured based on ratios and are adjusted to be dollar neutral, but not necessarily beta neutral through time. To construct industry neutrality, the value spreads are constructed by comparing the value measures within each industry.

EXHIBIT 14

Value Spreads for Hypothetical Industry-Neutral and Dollar-Neutral Value Portfolios (January 1990–May 2022)



Factor timing is always something investors consider when trying to enhance a multifactor investment portfolio. Of course, timing becomes a particularly enticing prospect during factor drawdowns, as investors wish to stem the bleeding and look for future opportunities to pick up additional expected returns. During these and other times, however, factor timing is not the only method investors seek to enhance returns. In addition to altering strategic weights of factors, or increasing or decreasing risk through timing, investors will consider different ways of tinkering or trading the factors. For example, measuring factor themes in new ways or how to combine factors and trade them will not only differ from the academic versions of the factors but will also differ across managers. For example, the signals used to form the factors, like value, can vary across managers. Some use the classic book-to-price ratio, others use cash flows, earnings, or sales to price. Others may define value within an industry to take out industry differences in accounting measures. As well, recent research has suggested that accounting for intangible assets is important in the new economy, with various ways of trying to account for this aspect (e.g., using intangible measures, industry neutralization, adding measures of quality, etc.). Indeed, many papers have been written on nuanced measures of the value theme.[52] Same goes for the other factors. Momentum can be based on price and fundamental-based measures (Chan et al. 1996; Novy-Marx 2015), quality can be based on various aspects related to growth, safety, payout, and profitability (Asness, Frazzini, and Pedersen 2019), and carry can be decomposed into static and dynamic components (Koijen et al. 2018). In addition, more and more managers are using proprietary datasets and augmented measures to construct stronger signals of these factors. All of these innovations to measurement have the potential to improve performance and, as alluded to previously, can provide a manager with a unique edge within factor investing. Again, this may be a form of "alpha" within the factor landscape. Of course, as in all attempts at alpha, it's a double-edged sword if you get it wrong.

[52] See, for example, Asness and Frazzini (2013), Blitz et al. (2014), Israel, Jiang, and Ross (2017), and Carvalho et al. (2017).

Managers will also differ on how they combine factors into a portfolio and how they trade them (Fitzgibbons et al. 2017; Israel, Jiang, and Ross 2017). These innovations can all add value but should not distract from the main point that simple factor exposure can improve investment portfolios. Often firms fight vigorously over their differences but tend to overlook the overwhelming commonality among them. The first-order effect on a portfolio is being exposed to factors, the second order effect is finding the best manager to do it (i.e., the manager who uses the best measures, best trading, implementation, etc.). Much like equity exposure, the most important decision is to figure out what exposure you want, and the second-order decision is to find the best manager to deliver it. Unfortunately, while the majority of a portfolio's performance will be driven by the first choice, most investors will spend most of their time and effort thinking about the second choice. Similar to factor investing, the main decision is to figure out what exposure you want to factors and then to consider the managers best positioned to deliver it. The differences among managers pale in comparison to the decision of whether to embrace factor investing generally.

Finally, timing, tinkering, or trading around a diversified strategic allocation is not free. It can incur costs from forgone diversification, can possibly miss the best months or exacerbate the worst ones, can add risk, and can add turnover and trading costs. It can also provide some benefits, too. Hence, the decision to time, tinker, or trade hinges on whether those benefits offset the costs. The bottom line is that disciplined strategic diversification across well-rewarded factors is a tough benchmark to beat.

#9. *Fiction*: You Know when You're in a Drawdown/Recovery and when to Cut/Add Risk

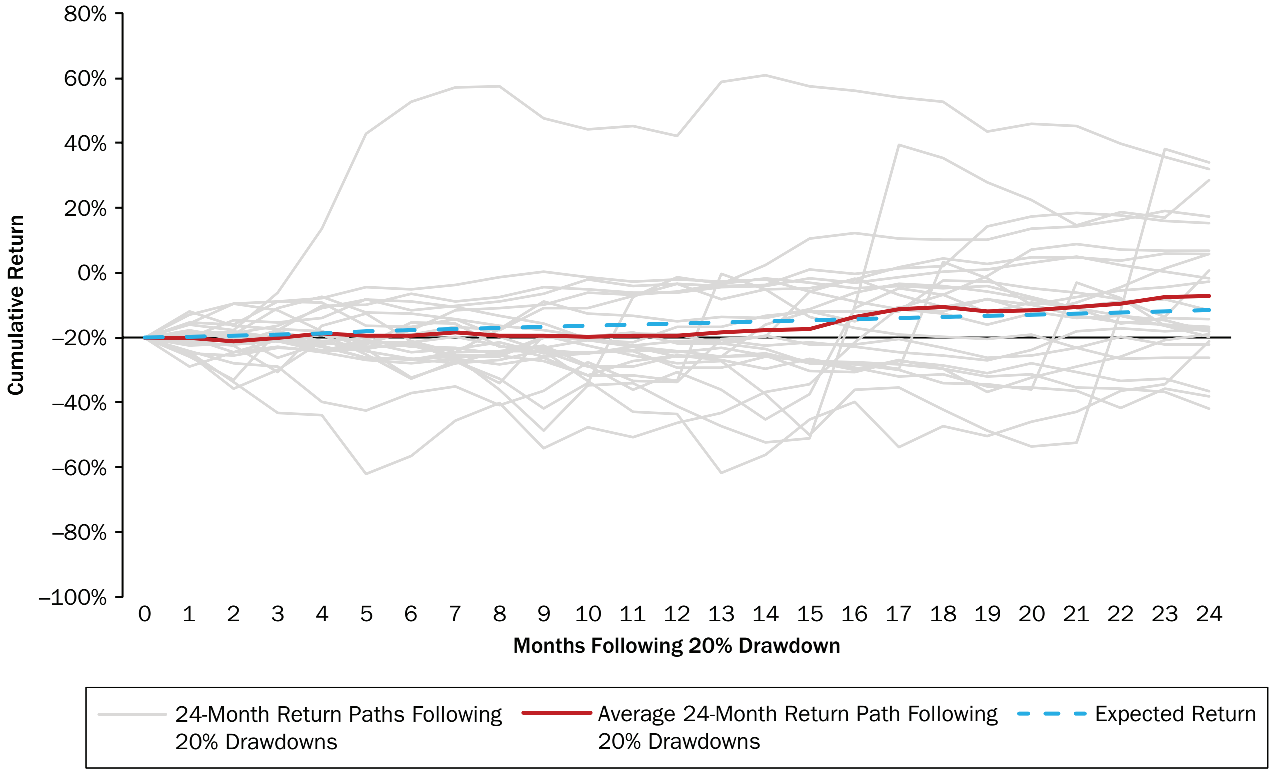
This fiction is just another variation on the misguided belief that factor timing is easy. Instead of focusing on timing of factor weights relative to each other, however, this myth focuses on timing the overall volatility (or tracking error) and dollar amount taken in the strategy as a whole. Plenty of investors try to time the overall market, with approaches like "buy the dip" or the opposite "take money off the table." In the midst of a drawdown, whether in the context of the market or an active strategy's performance, it's difficult to know when the trough is or how much worse it can get before it gets better.

Exhibit 15 illustrates this point in the context of a stock selection value strategy. Given value's much publicized drawdown from 2018 to 2020, and the severe and prolonged drawdowns it can experience generally, while still winning over the long term, value is a natural candidate factor to ask whether divesting during a drawdown and reinvesting during an apparent recovery can improve its long-term performance. The exhibit shows all the realized return paths in the 24 months following a 20% drawdown and highlights that the average return path is very similar to the path implied by the long-term expected return. In other words, knowing you are in a drawdown provides little information about subsequent expected returns—whether one is trying to stem the losses by reducing or capitalize on the losses by adding. It is really tough to know when to cut or add risk.

While Exhibit 15 illustrates the difficulty of knowing when to cut or add risk amid a drawdown purely by looking at past returns, this does not mean that there are not other tools that can help for this exercise. As explained in fact #8, in the context of the value factor, measuring the extent of the disconnect between prices and fundamentals can help better understand whether losses are more a function of predicting fundamentals incorrectly or more a function of price action with little changes in fundamentals. This approach still, however, offers no guarantee of success.

EXHIBIT 15

Stock Selection Value Strategy—Return Paths Following 20% Drawdowns (July 1926–August 2022)



In short, knowing when to cut or add risk is a very difficult exercise. As explained in the previous section (fact #8), our research shows that retaining consistent and disciplined exposure to a well-diversified multifactor portfolio is hard to beat.[53]

#10. *Fact*: Sticking with Factor Investing Is Hard, but Worth It

Although we have espoused the virtues of sticking with and being disciplined about factor investing, it is hard to do. If it were easy, everyone might do it! And, that is what creates those willing to hold the other side to provide a sustainable return premium going forward.

What makes sticking with it particularly difficult is that factor investing will inevitably experience drawdowns, but you will not know when (fact #2) or be able to time them well (fact #8 and fiction #9. Moreover, you will not have easy explanations for them (fact #2 and fiction #3).

What makes sticking with it particularly hard is that when factors suffer drawdowns, it can be difficult to answer the question "why" (or more accurately, "why now," aside from observing that investors should expect poor performance from time to time and very poor performance less often but unfortunately sometimes). Factors deviate from the market, and their risks are different than pure market risks. The benefit of this difference is diversification that improves the efficiency of a portfolio. The drawback of this difference is that there is often not an intuitive explanation for the poor performance beyond some obvious platitudes like "stocks selling at cheap

[53] While again admitting that when valuations (which are related to past returns but not the same) are at generational extremes, we do become a tad hypocritical here (Asness 2019).

multiples with high profit margins, low betas, and good price and fundamental momentum underperformed their industry counterparts." Consider the overall stock or bond market. When stocks in general suffer, one can usually point to the macroeconomy (e.g., slowed growth, a recession) as the culprit, or when bond markets suffer, one can point to the Fed and interest rates. But long–short market-neutral factors such as value or momentum? When they suffer, it is not easy to find a simple story. Indeed, these factors are often constructed to be relatively immune to the macroeconomy (covered in fact #4)—a benefit to the investment portfolio but a detriment to finding an intuitive, easy story for why the investment might be struggling right now. Put differently, *The Wall Street Journal* and CNBC have a lot of talking points for why stocks and bonds move, but fewer for why stocks with certain characteristics move relative to others. Factor performance is difficult to explain in the short run and hence can be difficult to stick with when suffering. This is both a curse and blessing, as it makes factors more difficult to stick with during the difficult times (that's the curse), but this is what allows factors to bring much-needed diversification to investors' portfolios (the benefit).[54] Little in life is free! Perhaps unintuitively, multifactor portfolios are even harder to stick with than single factors, as a multifactor process lacks by design simple one-line explanations to understand performance, and storytelling becomes harder.

Finally, and most frustratingly, even when they do recover after a drawdown, the recovery will not be smooth and easy. The market, after factors have been out of favor, does not apologize and return all the losses in a day, and even in long protracted large recoveries there will be periods of pain. All of this makes sticking with factor investing tough but commensurate with long-term rewards.

Consider the most recent value drawdown from 2018 to 2020 (there have been others over the last century and for the other factors, too, with the lessons being similar). In early 2020, two years into the drawdown, the cheapness of value was near extremes and the anticipation of a near-term recovery seemed reasonable. Yet, value continued to suffer for more than a year, exacerbating the pain of losses, but perhaps more importantly taking a psychological toll on investors anticipating a recovery. Sticking with it and more generally with factor strategies proved difficult for both practical and human reasons. On the practical side, leverage, risk, and cash constraints forced some investors to capitulate as the drawdown continued. On the human side, investors and their clients grew increasingly frustrated, and many threw in the towel. Frankly, the human side was by far the more important (few investors literally "had" to cover!).

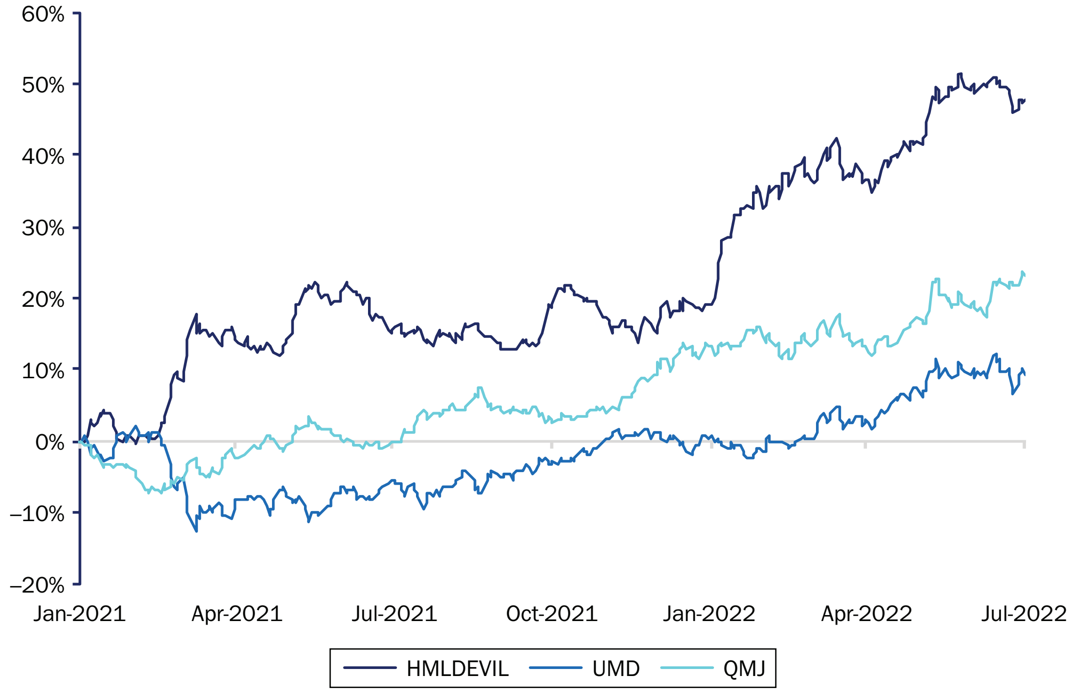
These frustrations are exacerbated when the market itself is doing well. The period from 2018 to 2020 was a prime example of factors suffering while general equity markets soared. Factor investors not only had a hard time explaining their duress, but they were also being doubly questioned when everyone else was making money in the market. That's a particularly tough time to stick with it—although from a portfolio perspective actually the least bad time to suffer.

Eventually, factors tend to recover from these drawdowns and have started to do so in 2021 and especially so in 2022. However, recovery is not always smooth and steady. Even during 2022 when factor investing is experiencing one of its best years ever, the daily returns are choppy with a lot of uncertainty. Exhibit 16 plots the daily returns of academic versions of stock selection value (HMLDEVIL), momentum (UMD), and quality (QMJ) strategies from January 1, 2021, to August 30, 2022. Despite the factors experiencing meaningful returns over this period, especially value with more

[54] An additional benefit is that the lack of being able to stick to it because factor drawdowns do not often have an easy story to them also likely prevents factors from getting "too crowded" or priced away. The very pain and difficulty are likely a large contributor to the factors not going away over time.

EXHIBIT 16

Stock Selection Factors—Cumulative Daily Returns (January 2021–August 2022)



than 40% cumulative return, notice how many days each factor experienced losses. That unsteady and volatile experience also makes it hard to stick to factor investing, even during the recovery periods when things are overall going well.

And this is why not everyone can (or should) be factor investors. It is why we should not worry too much about crowding into factors (although it should always be at least monitored) and why factors being widely known is not an issue. It is also why we continue to write about factor investing and seek to understand it better. And, it is why there is a reward to factor investing.

CONCLUSION

Factor investing has been around for a long time, backed by an enormous body of literature. This longevity and the collective insights have not prevented confusion and myths from arising again and again, often in the context of challenging performance. We hope to have cleared up some of that confusion by addressing many of the facts and fictions regarding factor investing, highlighting the evidence and where to find it (and replicate it).

As we have said in our other fact and fiction pieces, if one wishes to challenge the evidence, that is fine, too. As always, we welcome new challenges and debates and especially new evidence and ideas, even if they run counter to some of our own views. We wish to learn.

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