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The Quant Cycle

David Blitz

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The Quant Cycle

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KEY FINDINGS

- Major turning points in factor returns are not explained by traditional business cycle indicators but seem to be driven by abrupt changes in investor sentiment.
- We infer a simple three-stage quant cycle model directly from factor returns and show that it captures a considerable amount of time variation in factor returns.
- Key stages in the model are value factor drawdowns, either due to rallies of growth stocks or crashes of value stocks, and subsequent reversals.

ABSTRACT

Traditional business cycle indicators do not capture much of the large cyclical variation in factor returns. Major turning points of factors seem to be caused by abrupt changes in investor sentiment instead. The author infers a quant cycle directly from factor returns, which consists of a normal stage that is interrupted by occasional drawdowns of the value factor and subsequent reversals. Value factor drawdowns can occur in bullish environments due to growth rallies and in bearish environments due to crashes of value stocks. For the reversals, the author also distinguishes between bullish and bearish subvariants. Empirically, he shows that his simple three-stage model captures a considerable amount of time variation in factor returns. The author concludes that investors should focus on better understanding the quant cycle as implied by factors themselves, rather than adhering to traditional frameworks that, at best, have a weak relation with actual factor returns.

The factors in asset pricing models exhibit cyclical behavior, offering a premium in the long run but going through bull and bear phases in the short run. For instance, the HML value factor of Fama and French (1993) has a long-term premium of about 3%, but had a –20% annual return over the 1998–1999 period, followed by a +15% annual return over the 2000–2006 period. What explains these cyclical dynamics of factors?

From a rational asset pricing perspective, factor premiums are risk premiums, reflecting rewards for certain macroeconomics risks. This would imply that factor performance is related to the business cycle. For instance, in their seminal paper on the size and value premiums, Fama and French (1992) already mentioned that "examining the relations between the returns on these portfolios and economic variables that measure variation in business conditions might help expose the nature of the economic risks captured by size and book-to-market equity." Many studies have since attempted to establish a robust empirical link between factors and the business cycle, but this has not proven to be easy. A recent example is by Ilmanen et al. (2021), who examined more than a dozen macroeconomic variables related to business cycles, growth, and monetary policy but found that none of these are very effective in explaining, let alone predicting, factor returns.

Perhaps it is so difficult to establish a relation between macroeconomic risks and factor premiums because the notion that factor premiums are risk premiums at heart is flawed. If the source of factor premiums is behavioral instead, then we may need to look in a different direction for a proper understanding of the time variation in factor returns. For instance, Stambaugh, Yu, and Yuan (2012) reported a strong link between factor returns and the investor sentiment index of Baker and Wurgler (2006). We confirm that this behavioral indicator captures more cyclical variation in factor premiums than traditional business cycle indicators. However, computing sentiment scores in real time is not easy, the scores can be counterintuitive, and, most importantly, the discriminatory power of investor sentiment remains limited because expected factor premiums are still positive in all scenarios.

Inspired by these results, we argue that factors essentially follow their own cycle, which can be inferred from their realized returns. Following this approach, we identify a cycle consisting of a normal stage that is interspersed with occasional large drawdowns of the value factor, which tend to be followed by reversals. The normal stage prevails about two-thirds of the time. Drawdowns of the value factor are caused by rallies of growth stocks or crashes of value stocks that occur about once every 10 years and typically last about 2 years. The large losses on the value factor during these periods are oftentimes mirrored by similar-sized gains on the momentum factor. Growth rallies and value crashes are typically followed by violent reversals, which are characterized by either a crash of the growth stocks that went up strongly in the previous stage or a strong recovery rally of stocks that underperformed in the previous stage. Empirically, we show that this simple three-stage quant cycle is able to capture a huge amount of time variation in factor returns.

We conclude that, to understand the cyclical dynamics of factors, investors should recognize that factors follow their own sentiment-driven cycle. Traditional business cycle and sentiment indicators may pick up some of these dynamics, but their practical usefulness is limited. By inferring the quant cycle directly from factor returns, we are able to capture much more time variation. The practical implication for investors is that they should focus their efforts on better understanding the quant cycle as implied by factors themselves, rather than adhering to traditional frameworks that, at best, have a weak relation with actual factor returns.

DATA

Our main analysis focuses on four factors that are frequently targeted by investors: value, quality, momentum, and low risk. For each factor, we consider two definitions. For value, we use the HML value factor of Fama and French (1993), which is based on the book-to-market ratio, and the CMA investment factor of Fama and French (2015), which is based on growth in total assets. Fama and French (2015) found that their new CMA factor fully subsumes their classic HML factor, so it can be interpreted as a superior value metric. Blitz and Hanauer (2021a) also treated CMA as a substitute for HML. For quality, we use the RMW profitability factor of Fama and French (2015), which is based on operating profitability, and the quality-minus-junk (QMJ) factor of Asness, Frazzini, and Pedersen (2019), which is based on about 20 different quality metrics. For momentum, we use the WML momentum factor of Carhart (1997), which is based on past 12-1M returns, and the iMom idiosyncratic (or residual) momentum factor of Blitz, Huij, and Martens (2011) and Blitz, Hanauer, and Vidojevic (2020), which isolates the nonsystematic part of past 12-1M returns.

Finally, for low risk, we use the VOL factor of Blitz, van Vliet, and Baltussen (2020), which is based on past 36-month volatility, and the betting-against-beta (BAB) factor of Frazzini and Pedersen (2014), which is based on betas with a lookback period of one year for the volatility component and five years for the correlation component. In addition to these 4×2 individual factors, we also consider an equally weighted (1/N) mix of these eight factors.

All factors are based on capitalization-weighted 2×3 sorted portfolios as done by Fama and French (1993), except BAB. Novy-Marx and Velikov (2021) showed that the BAB premium is inflated by the nonstandard methodology used to construct this factor, which should be kept in mind when comparing it with the other factors. We use the US versions of all factors, with monthly data from July 1963 to December 2020, which is the longest period for which data for all factors are available. For completeness, we also report the results for the market factor (market return in excess of the return on risk-free Treasury bills) and the SMB size factor. Although the size factor has a solid place in academic asset pricing models, Blitz and Hanauer (2021b) showed that the size premium has failed to materialize since its discovery about 40 years ago and that, if there is a size premium at all, it is beyond the reach of investors. All data are sourced from the online data libraries of Kenneth French,[1] Robeco,[2] and AQR.[3]

We extend our analysis to the January 1929 to June 1963 pre-sample period for a reduced set of factors that are available over this time frame. We also extend the analysis over our main sample period to a set of alternative asset pricing factors. From the Kenneth French data library, we consider alternative value factors based on the earnings-to-price (E/P) or cash-flow-to-price (CF/P) ratios, the long-term reversal factor (LTR), and the short-term reversal factor (STR). We also examine the return-on-equity (ROE) and expected growth (EG) factors from the q-factor model of Hou, Xue, and Zhang (2015) and Hou et al. (2021), available from January 1967 to December 2020,[4] and the post–earnings announcement drift (PEAD) and financing (FIN) factors from the behavioral asset pricing model of Daniel, Hirsleifer, and Sun (2020), available from July 1972 to December 2018.[5] Finally, we consider the conservative minus stable (CMS) factor of Blitz and van Vliet (2018), sourced from the online data library of Robeco.

RESULTS FOR TRADITIONAL METRICS

We start by briefly examining the performance of factors in different macroeconomic environments. The scope of this analysis is limited to establishing that the results for our sample are generally similar to the existing literature. To this end, we consider National Bureau of Economic Research (NBER) expansions versus recessions, inflation regimes, ISM purchasing managers sentiment, and the Baker and Wurlger (2006) investor sentiment measure. For a more comprehensive analysis of the relation between factors and all kinds of macroeconomic indicators, we refer to studies such as that by Ilmanen et al. (2021).

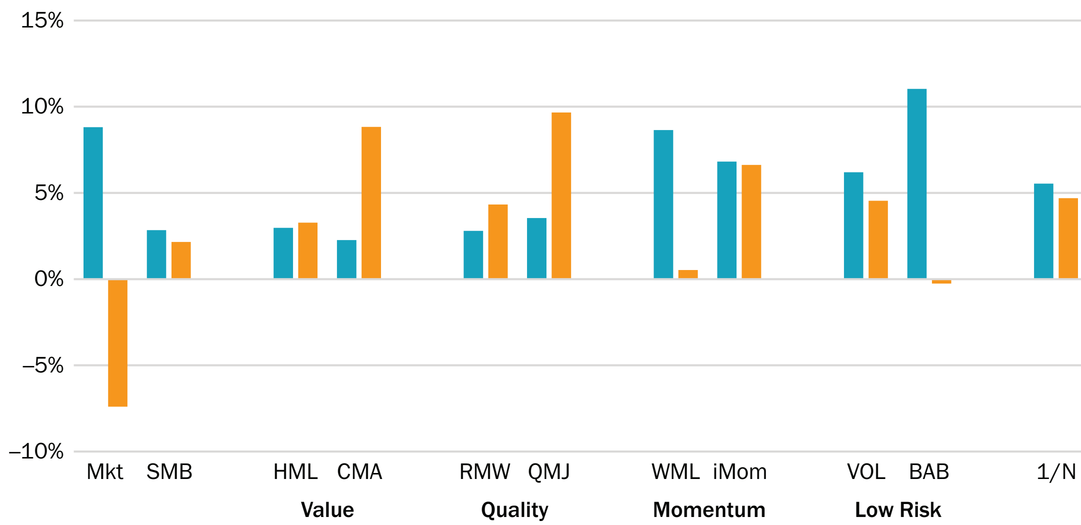
Exhibit 1 shows when the US economy is officially in recession according to the NBER, which amounts to 12% of the time on average. Exhibit 2 shows the annualized return of factors during expansions versus recessions. For the market factor, we observe a large return spread, with an average return of 8.8% during expansions versus –7.4% recessions. For the other factors, however, the indicator is much less relevant. For instance, the HML return is almost exactly the same in both environments. Only the BAB factor shows a marginally negative return during recessions. However, the other low-risk metric, VOL, hardly exhibits this sensitivity. Altogether, the 1/N mix has virtually the same return during expansions and recessions.

EXHIBIT 1

NBER Business Cycle: Expansions versus Recessions

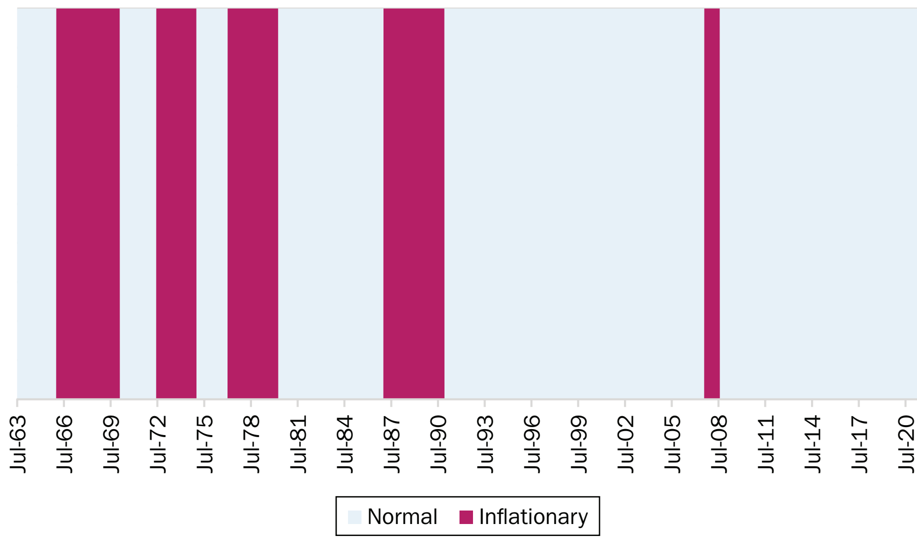
EXHIBIT 2

Factor Returns during Expansions versus Recessions, July 1963–December 2020



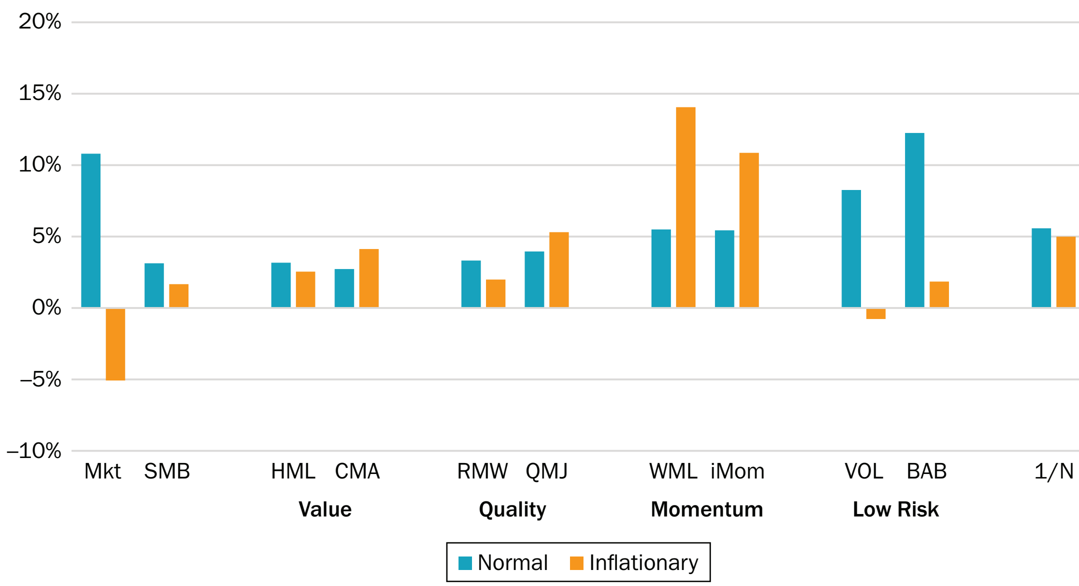
Neville et al. (2021) examined the performance of investment strategies during inflationary versus non-inflationary periods. They defined inflationary regimes as the times when headline, year-over-year inflation is accelerating and the level exceeds 5%. Following their exact regime classification, Exhibit 3 shows that inflationary periods make up 25% of our sample. Neville et al. (2021) found that equities and bonds have large negative returns during inflationary periods but that trend-following strategies generally do well in such an environment. Exhibit 4 confirms these conclusions for our sample, with an average market return of –5.1% and double-digit positive returns for the momentum factors during inflationary periods. The two low-risk factors struggle during inflationary periods, which is consistent with their known bond-like properties

EXHIBIT 3
Inflation Cycle



SOURCE: Neville et al. (2021).

EXHIBIT 4
Factor Returns during Normal versus Inflationary Periods, July 1963–December 2020



(see, e.g., Blitz 2020) and the finding of Neville et al. (2021) that bonds have large negative returns during inflationary periods. The value and quality factors appear largely immune to inflationary versus non-inflationary conditions, however. Altogether, the simple 1/N mix is again remarkably stable, with practically the same return in both regimes.

We next consider the ISM purchasing managers index, which is a widely followed sentiment indicator for the state of the US economy. We distinguish between ISM levels above and below 50, which denote an optimistic versus a pessimistic outlook. Exhibit 5 shows that the pessimistic state occurs 27% of the time over our

EXHIBIT 5

ISM Business Outlook

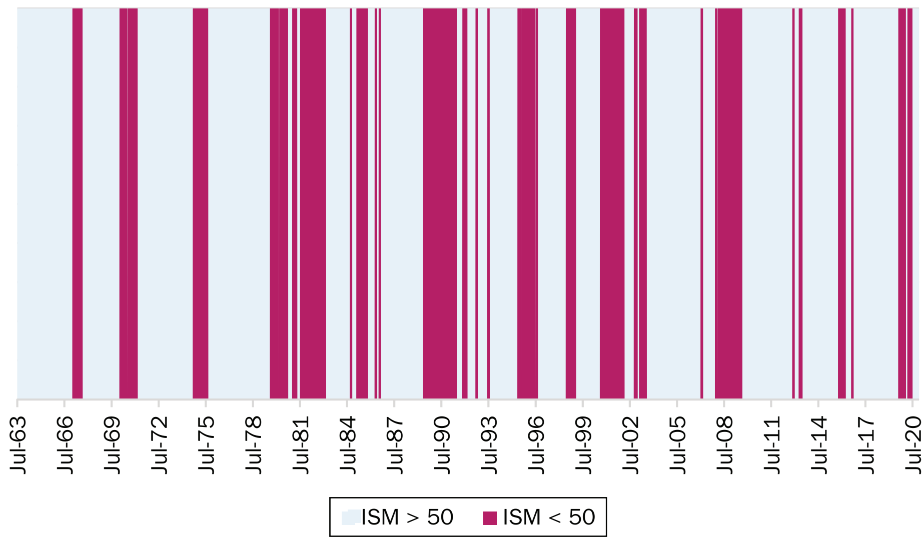
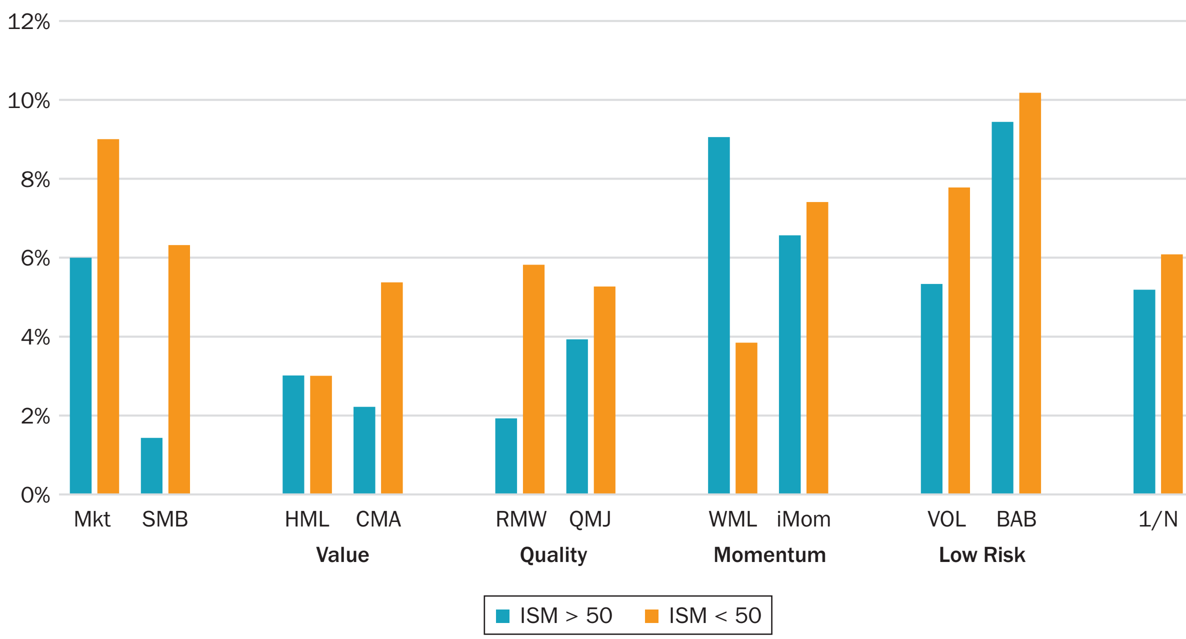


EXHIBIT 6

Factor Returns Conditional on ISM Business Outlook, July 1963–December 2020



sample. Exhibit 6, however, shows that there is little relation with factor returns. Factor returns generally appear to be solid regardless of whether the ISM business outlook is optimistic or pessimistic, and the 1/N mix again has virtually identical returns in both states.

EXHIBIT 7
Investor Sentiment

NOTE: Based on Baker and Wurgler (2006).

A popular sentiment indicator in the academic literature is the investor sentiment index of Baker and Wurgler (2006). The current version of this sentiment index is based on five sentiment indicators, namely the value-weighted dividend premium, first-day returns on initial public offerings (IPOs), IPO volume, the closed-end fund discount, and the equity share in new issues. Data are available from July 1965 until the end of 2018 on the homepage of Jeffrey Wurgler.[6] A visual illustration is given in Exhibit 7, which shows that positive and negative investor sentiment each occur about 50% of the time on average. Stambaugh, Yu, and Yuan (2012) found that factor returns are much higher when sentiment is positive than when it is negative. Exhibit 8 confirms this result for the value, quality, and low-risk factors, which each show strong returns when investor sentiment is positive and weak returns when investor sentiment is negative. Only the momentum factors appear to be resilient to the sentiment states. Interestingly, the size factor and the market factor do better when sentiment is negative.

Compared to the previously discussed business cycle and macroeconomic indicators, the investor sentiment index appears to be more effective at identifying high versus low factor returns. However, it also has several drawbacks. First, computing investor sentiment scores in real time is not easy, given the required inputs. Second, the scores can be counterintuitive. For instance, the last 10 years of the available sample (2009–2018) were basically one big bull market, yet the sentiment indicator was predominantly negative (70% of the time). Third, even though investor sentiment may be more effective than the other metrics, its discriminatory power remains limited because expected factor premiums are still positive in all instances.

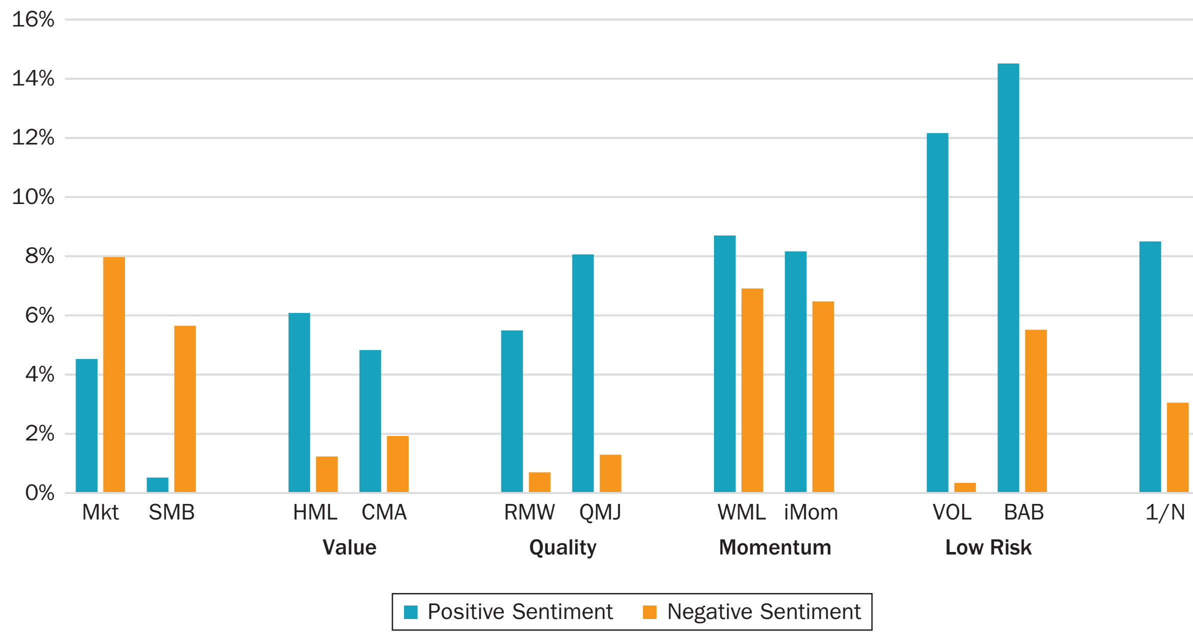
DEFINING THE QUANT CYCLE

Perhaps it is so difficult to establish a relation between macroeconomic risks and factor premiums because the notion that factor premiums reward investors for bearing

[6] https://pages.stern.nyu.edu/~jwurgler/.

EXHIBIT 8

Factor Returns Conditional on Investor Sentiment, August 1965–December 2018



such risks is flawed. For instance, the major turning points in the factor cycle do not appear to coincide with the release of major macroeconomic news but seem to be related to changes in investor sentiment. In retrospect, it is unclear what triggered these sentiment changes, and it seems that they might as well have happened at an earlier or later point in time. Apart from that, there is of course also the entire behavioral finance literature, which links factor premiums to psychological biases in the human decision-making process.

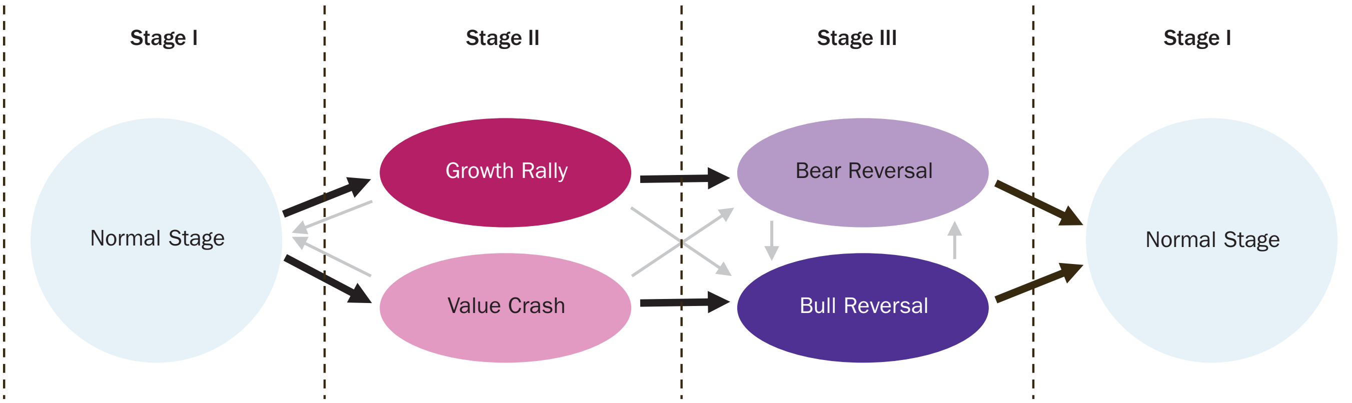
If the source of factor premiums is indeed behavioral, this would explain why the Baker and Wurgler (2006) investor sentiment index appears more effective at distinguishing between high and low factor returns. However, even this indicator is only able to pick up a small portion of the much larger time variation in factor returns. In this section, we argue that the cyclicality in factor returns is driven by sentiment, which can best be inferred directly from factor returns, instead of relying on various indirect indicators. In other words, our premise is that factors essentially follow their own behavioral cycle, and although other macroeconomic and behavioral indicators may pick up some of these dynamics, the full picture can only be uncovered by studying factors themselves.

We determine the quant cycle by qualitatively identifying peaks and troughs that correspond to bull and bear markets in factor returns. Our approach is part art and part science, similar to the fact that there is no universally accepted definition of the bull and bear markets of the equity market. For instance, how deep and how long does a drawdown need to be to qualify as a true bear market as opposed to a temporary correction during a bull market? The quant cycle proposed in this article may be seen as a first attempt at describing the cyclicality in factor returns. We believe that this is already very insightful, but we fully acknowledge that others might prefer to change, add, or remove certain breakpoints and perhaps use more sophisticated methodologies.

For defining the quant cycle, we focus more on volatile factors, such as value and momentum, than on factors such as quality that exhibit much less extreme return swings. Looking at the value factor, we observe that it experiences a major drawdown about once every 10 years. The cause for these drawdowns is either a rally of growth

EXHIBIT 9

Conceptual Illustration of the Quant Cycle



stocks (in a bullish environment) or a crash of value stocks (in a bearish environment). These periods also tend to be tough for the low-risk factor. However, as also observed by Blitz (2021), large losses on the value factor are oftentimes mirrored by similar-sized gains on the momentum factor.

Immediately following a growth rally or value crash, we typically observe a strong reversal. Here it is even more important to distinguish between bullish and bearish variants because their impact on factor returns is very different. The first variant, which we will call a *bear reversal*, is characterized by a crash of the growth stocks that rallied during the previous stage, resulting in a strong rebound of the value factor. An example of this is the burst of the tech bubble in 2000–2002, during which the NASDAQ lost over three-quarters of its value. The second variant, which we call a *bull reversal*, is characterized by a rebound of the stocks that experienced the biggest losses, resulting in large negative returns for the momentum factor. An example of this is the relief rally of 2009, when cheap financials that were beaten down during the Global Financial Crisis made a strong recovery. A bull reversal can also follow a bear reversal, if growth stocks that have been massively sold off bounce back again, as in 2002–2003. Bear reversals tend to be great for multifactor investors, with large positive returns on all factors, but bull reversals are much more challenging, with large negative returns for most factors except value.

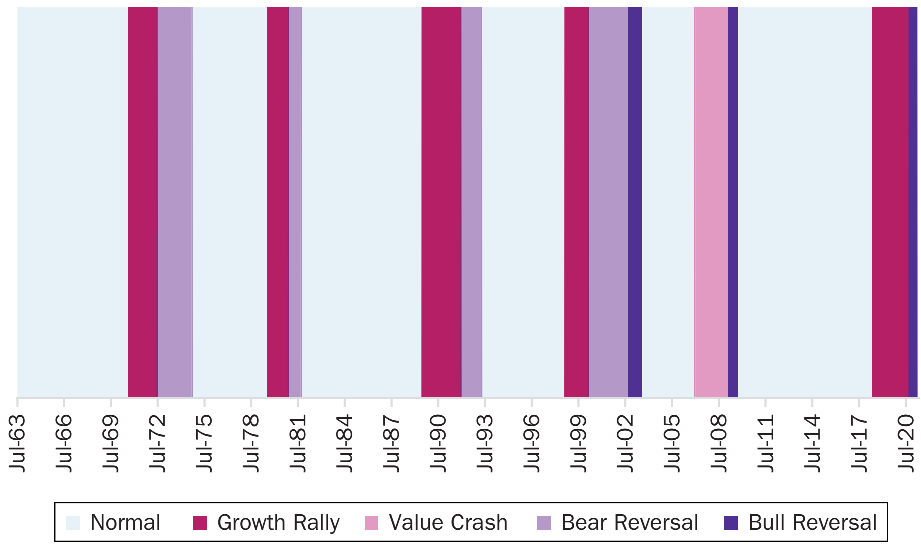
After the reversal stage, factors tend to revert back to normal mode, which is the stage that actually prevails about two-thirds of the time. A conceptual illustration of the quant cycle is given in Exhibit 9. Bright coloring denotes bullish stages, and subdued coloring denotes bearish stages. Similarly, dark arrows denote the most common transitions between the different stages, and light arrows denote alternative, less likely transitions.

RESULTS FOR THE QUANT CYCLE

Our historical definition of the quant cycle is depicted in Exhibit 10. We observe that about once every 10 years the normal stage is interrupted by growth rallies or value crashes that last about 2 years and are in turn followed by reversals. Interestingly, this tends to happen around the turn of the decade, similar to the NBER recessions shown before in Exhibit 1. Thus, there might be some kind of link between factor dynamics and the macroeconomy after all. However, whereas NBER recessions have very little discriminatory power for factor returns, the quant cycle has very strong explanatory power, as we will see shortly. Thus, the differences between the

EXHIBIT 10

The Quant Cycle 1963–2020



quant cycle and the official business cycle overwhelm the impact of any perceived similarities.

The first growth rally is the Nifty Fifty era in the early 1970s, during which investors flocked to blue-chip stocks such as Xerox, Polaroid, Coca-Cola, McDonalds, and IBM. The second growth rally is in 1979–1980 and was driven by the energy and materials sectors, which benefited from rising oil and commodity prices due to the second oil crisis. Starting at the end of the 1980s, we have another growth rally, this time powered by the health care, biotech, and beverages industries. All these growth rallies are followed by bear reversals. The next growth rally is the infamous tech bubble in the late 1990s, which was also followed by a bear reversal from 2000 to 2002. Immediately afterward, in 2002–2003, we observe a bull reversal, when the most oversold growth stocks bounced back again.

The next drawdown of the value factor is during the 2007–2009 Global Financial Crisis. However, this time the cause is not a rally of growth stocks but a crash of value stocks, in particular financials. It is followed by a bull reversal in 2009 of the same beaten down financials. Finally, we have the 2018–2020 growth rally that was driven by technology stocks such as FANMAG and Tesla, resulting in what Blitz (2021) dubbed the "quant crisis." It was followed in late 2020 by a bull reversal of value stocks, which was ongoing at the end of our sample in December 2020.

Exhibit 11 reports the performance of factors during the various stages of the quant cycle. All returns are annualized, unless the period is shorter than 12 months, in which case we report cumulative returns. During the normal stage, all factors show solid positive average returns, typically even above their long-term average premiums. Looking at the individual normal periods, we also see predominantly positive returns, with negative returns being few in number and small in magnitude. Luckily for multifactor investors, this stage prevails about two-thirds of the time. However, the relative peace and quiet of the normal period is upset by the events that unfold during the remaining one-third of the time.

Growth rallies are characterized by large negative returns for the value factors and large positive returns for the momentum factors, in particular HML and WML. These periods clearly illustrate why the value–momentum combination is at the heart of many quant approaches, because the two factors diversify so well with each other

EXHIBIT 11

Factor Returns over the Quant Cycle 1963–2020

		Market	Size	Value		Quality		Momentum		Low Risk		
		Mkt-RF	SMB	HML	CMA	RMW	QMJ	WML	iMom	VOL	BAB	1/N
Full Sample	All	6.8	2.8	3.0	3.1	3.0	4.3	7.6	6.8	6.0	9.6	5.4
Normal	All	10.0	3.0	4.7	2.9	2.4	3.7	6.9	5.3	9.0	13.2	6.0
	July 1963–August 1970	1.8	6.6	5.5	3.0	0.3	2.9	8.7	6.5	–0.6	5.4	4.0
	October 1974–July 1979	12.5	14.2	6.5	3.2	–1.6	–2.6	5.4	6.5	2.5	12.8	4.1
	October 1981–June 1989	10.2	–0.6	7.8	7.0	5.2	7.2	7.4	8.0	17.4	17.9	9.7
	May 1993–August 1998	11.8	–5.0	5.0	2.3	6.0	7.5	11.0	9.4	13.2	17.8	9.0
	August 2003–December 2006	10.7	4.2	9.5	0.7	2.6	–1.4	2.0	3.3	14.8	19.3	6.3
	October 2009–May 2018	13.8	1.2	–1.7	0.0	1.5	4.7	5.2	–0.2	8.3	10.4	3.5
Growth Rally	All	15.5	1.0	–19.5	–5.8	1.3	3.5	19.7	11.2	–9.3	–6.2	–0.6
	September 1979–June 1972	15.8	6.8	–10.7	–5.6	9.4	6.4	9.6	11.3	6.1	6.1	4.1
	August 1979–November 1980	21.3	8.0	–24.4	–10.4	11.5	1.5	43.0	27.6	–17.2	–1.4	3.8
	July 1989–December 1991	8.0	–5.4	–11.5	–3.9	8.1	11.5	18.2	13.9	3.4	–1.1	4.8
	September 1998–February 2000	28.2	16.9	–34.1	–7.9	–32.9	–9.5	34.4	16.0	–56.0	–49.1	–17.4
	June 2018–September 2020	11.6	–11.0	–22.9	–3.8	3.8	2.3	6.6	4.3	–0.5	3.5	–1.9
Value Crash	All	–28.2	–2.0	–15.3	–2.0	13.4	22.0	19.4	8.2	–5.4	–15.9	3.1
	January 2007–February 2009	–28.2	–2.0	–15.3	–2.0	13.4	22.0	19.4	8.2	–5.4	–15.9	3.1
Bear Reversal	All	–20.5	0.5	28.4	16.6	10.3	11.6	10.4	13.7	17.0	24.9	16.6
	July 1972–September 1974	–28.9	–10.7	23.7	15.8	–5.4	3.8	18.8	12.8	0.5	–1.3	8.6
	December 1980–September 1981	–25.5	5.5	27.5	10.7	–6.3	3.3	–20.0	6.6	16.4	21.1	7.4
	January 1992–April 1993	4.8	4.8	27.9	11.5	0.1	–4.8	11.0	12.0	8.6	32.9	12.4
	March 2000–September 2002	–22.9	6.1	31.4	21.2	35.2	29.2	13.9	17.2	34.8	43.5	28.3
Bull Reversal	All	46.6	24.2	10.3	7.6	–18.3	–32.3	–71.5	–16.9	–5.8	–9.7	–17.1
	October 2002–July 2003	22.7	11.7	–7.3	9.7	–19.7	–18.2	–29.2	–6.7	11.3	–13.2	–9.2
	March 2009–September 2003	39.9	12.5	19.7	2.4	–5.3	–26.0	–72.3	–17.5	–19.2	–1.2	–14.9
	October 2020–December 2020	15.0	16.2	4.8	0.5	–5.5	–9.5	–17.7	–4.0	–1.7	–1.7	–4.4

during these extreme times. As also observed by Blitz (2021), the momentum gains during growth rallies typically offset the value losses, with the notable exception of the 2018–2020 quant crisis. Not surprisingly, the idiosyncratic momentum factor is less strong than standard momentum during growth rallies; by avoiding systematic style biases, it cannot benefit from a pronounced growth tilt. During growth rallies, the low-risk factors typically take a hit, although not in every instance. Quality factors usually do well, although again not always. Altogether, the 1/N mix has a flat return on average during growth rallies. The sample only contains a single value crash, namely the 2007–2009 Global Financial Crisis. Although the market return is very different compared to the growth rallies, factor performance is remarkably similar, with negative returns for value and low risk and positive returns for momentum. Based on this single observation, quality seems to do better during value crashes, resulting altogether in a small positive return for the 1/N mix.

Finally we have the two types of reversals. Bear reversals are characterized by large positive returns for the value factor owing to a crash of growth stocks, whereas bull reversals are characterized by large negative returns for the momentum factor owing to a rally of stocks with poor momentum. Bear reversals (i.e., crashes of growth stocks) tend to be highly favorable for the quality, momentum, and low-risk factors. Thus, all factors tend to be effective during these periods, resulting in spectacular returns for the 1/N mix. However, the market shows a large negative return. For bull reversals (i.e., momentum crashes), the picture is completely different, with large negative returns for the quality factor and mixed results for the value and low-risk factors. During these episodes, idiosyncratic momentum shines compared to generic momentum by severely limiting the losses. Still, bull reversals present much tougher challenges for multifactor investors than bear reversals, and the 1/N mix shows a large negative average return. The market and size factors show opposite behavior, with strong positive returns in this scenario.

Zooming in on the individual growth rally, bear reversal, and bull reversal periods, we observe generally consistent results, although there are of course some exceptions. For instance, quality factors typically do well during growth rallies but had a large negative return during the 1998–2000 tech bubble, whereas their strong performance during bear reversals appears to be mostly driven by the 2000–2002 tech bubble burst episode. In addition, momentum usually does well during bear reversals, but the 1980–1981 episode was an exception to the rule. And although low-risk factors typically do badly during bull reversals, they actually did well during the 2002–2003 reversal. This may be explained by the fact that this was a relief rally of growth stocks that had taken a big beating in previous years, whereas the other bull reversals are relief rallies of value stocks. These exceptions notwithstanding, the simple quant cycle model offers vastly improved explanatory power and robustness compared to the common macroeconomic indicators discussed earlier.

Exhibit 12 reports the frequency of the various stages of the quant cycle, and Exhibit 13 shows the (unconditional) probability of transitioning from one stage to another over a 12-month period. For the latter analysis, we focus on the three high-level stages shown in Exhibit 9; that is, we combine the two difficult periods for the value factor, growth rallies and value crashes, and we combine the two types of reversals. We estimate an unconditional probability of 16% for

EXHIBIT 12

Frequency of Quant Cycle Stages 1963–2020

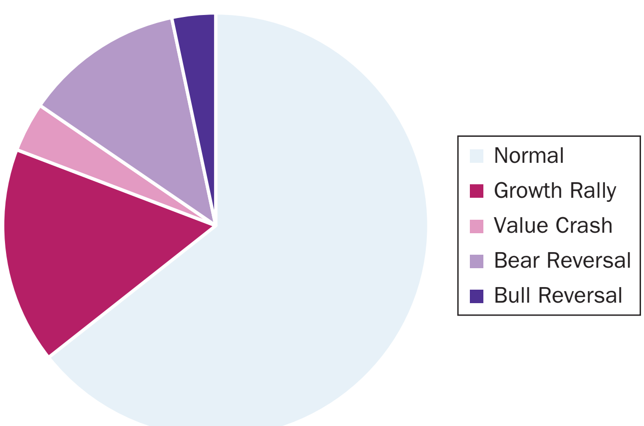


EXHIBIT 13

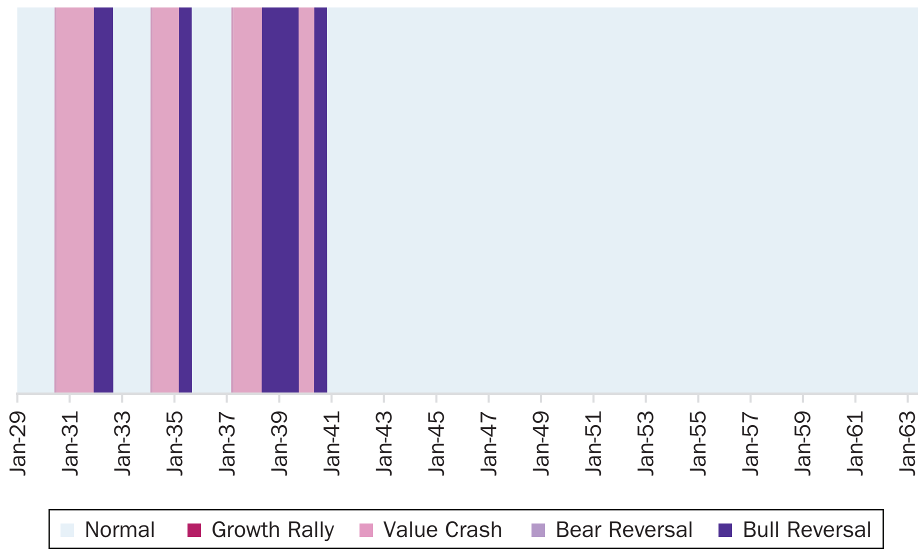
12-Month Transition Probabilities 1963–2020

		To		
		Stage I	**Stage II**	**Stage III**
From	Stage I	84%	16%	0%
	Stage II	5%	52%	43%
	Stage III	52%	0%	48%

NOTE: Stage I refers to the normal stage, stage II refers to a growth rally or value crash, and stage III refers to a bear or bull reversal.

EXHIBIT 14

The Quant Cycle 1929–1963



transitioning from the normal stage to a growth rally or value crash within one year, consistent with the average length of the normal stage being about six years. The growth rallies, value crashes, and reversals tend to be much shorter, resulting in a probability of about 50% for moving to the next stage within a year. Some transitions have a zero estimated probability because they have not occurred over our sample period, but of course, this does not mean that they are impossible, as also illustrated by the light arrows in Exhibit 9.

We conjecture that conditional probabilities can be quite different from the unconditional probabilities shown in Exhibit 13. For instance, a transition from the normal stage to a growth rally or value crash within the next 12 months is probably much more likely if the normal stage has continued for more than five years compared to having just started. However, the number of stage transitions is insufficient for reliably estimating conditional transition probabilities.

THE QUANT CYCLE PRE-1963

The post-1963 sample period suggests that value crashes are extremely rare, because all but one of the major drawdowns of the value factor are the result of growth rallies. One might also get the impression that bull reversals are a relatively recent phenomenon because they are all concentrated in the later part of the sample. However, by going back further in time, in particular to the Great Depression period of the 1930s, we can uncover many more value crashes and bull reversals.

Exhibit 14 shows an extension of the quant cycle to the 1929–1963 period. During the 1930–1940 Great Depression period, we observe no less than four value crashes and subsequent bull reversals taking place in quick succession. In one case, a bull reversal is even followed immediately by another value crash, without a return to normal in between. This turbulence stands in stark contrast to the subsequent decades: From late 1940 onward, we observe an unusually long normal period without any major factor drawdowns. Altogether, the number of value factor drawdowns and reversals observed over the 1929–1963 sample is roughly equal to what we would expect based on a frequency of about once every 10 years; however, they are very unevenly distributed over this sample. Note also that we do not observe any growth

EXHIBIT 15
Factor Returns over the Quant Cycle 1929–1963

		Market	Size	Value		Quality		Momentum		Low Risk		
		Mkt-RF	SMB	HML	CMA	RMW	QMJ	WML	iMom	VOL	BAB	1/N
Full Sample	**All**	**9.2**	**2.7**	**5.7**	**–**	**–**	**–**	**7.3**	**8.5**	**6.0**	**5.6**	**6.6**
Normal	**All**	**13.3**	**2.2**	**8.1**	**–**	**–**	**–**	**10.2**	**9.2**	**7.9**	**7.0**	**8.7**
	January 1929–June 1930	–14.0	–25.4	8.8	–	–	–	22.1	11.1	17.3	–	15.7
	September 1932–February 1934	33.6	30.2	7.6	–	–	–	8.2	28.2	13.4	3.30	16.3
	September 1935–March 1937	33.1	16.5	29.6	–	–	–	11.9	9.9	–2.7	4.0	13.7
	November 1940–June 1963	12.3	1.2	6.6	–	–	–	9.5	7.8	7.7	6.0	7.3
Growth Rally	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**
Value Crash	**All**	**–36.9**	**–3.2**	**–30.1**	**–**	**–**	**–**	**26.7**	**9.4**	**3.0**	**5.8**	**–2.4**
	July 1930–December 1931	–51.0	–0.1	–23.0	–	–	–	39.6	17.6	–13.0	–18.0	–2.9
	March 1934–March 1935	–12.9	8.0	–47.5	–	–	–	34.9	11.7	17.0	37.2	1.0
	April 1937–May 1938	–43.7	–16.9	–21.7	–	–	–	–0.2	–4.2	3.7	–0.9	–7.5
	October 1939–May 1940	–21.8	–3.0	–21.6	–	–	–	21.0	7.3	10.1	13.5	1.5
Bear Reversal	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**	**–**
Bull Reversal	**All**	**41.4**	**16.3**	**38.5**	**–**	**–**	**–**	**–51.8**	**–0.8**	**–8.4**	**–12.1**	**0.6**
	January 1932–August 1932	24.4	19.0	77.5	–	–	–	–73.4	1.4	–27.9	–38.6	2.7
	April 1935–August 1935	28.6	0.4	17.8	–	–	–	–18.2	8.1	3.2	5.3	5.7
	June 1938–September 1939	35.2	18.5	4.3	–	–	–	–34.1	–8.6	1.4	–4.9	–6.3
	June 1940–October 1940	17.4	2.3	8.0	–	–	–	–9.7	–0.2	–0.9	5.7	1.8

rallies and bear reversals over this period of more than 30 years. Thus, the apparent regularity observed post-1963 and the transition probabilities estimated over that period may not be representative for the long run.

Exhibit 15 reports factor performance during the various stages of the quant cycle for the 1929–1963 period. Unfortunately, data for one of the value factors, CMA, and both quality factors, RMW and QMJ, are not available for this early sample. For the remaining factors, the pre-1963 results are quite consistent with the post-1963 results. During normal periods, factor returns are solid. During value crashes, the large negative returns on the HML value factor are generally mirrored by similarly large positive returns on the WML momentum factor, whereas the iMom factor is again less strong. Low-risk factors provide some relief, on average. Altogether, the 1/N mix (with double weight for HML, because it is the only value factor, and without the quality factors) has a small negative return.

During bull reversals, we observe the characteristically large negative returns on the WML momentum factor and large positive returns on the HML value factor. As before in this scenario, the iMom factor massively outperforms the WML momentum factor, whereas the low-risk factors tend to take a hit. Combined, the 1/N portfolio shows a roughly flat return in this scenario, which is much better than for the post-

EXHIBIT 16

Alternative Asset Pricing Factors 1963–2020

Rank	E/P	CF/P	LTR	STR	ROE*	EG*	PEAD**	FIN**	CMS
Full Sample	3.1	2.9	2.3	5.8	6.1	9.7	7.4	9.0	13.0
Normal	4.3	3.9	1.9	7.3	5.9	8.8	5.9	7.7	14.2
Growth Rally	–15.6	–14.0	–5.8	0.4	9.5	9.0	16.1	–10.0	0.9
Value Crash	–6.5	–1.2	–6.5	–13.0	15.8	12.6	4.0	4.7	1.0
Bear Reversal	23.9	21.6	15.3	8.3	10.8	19.2	11.3	37.8	33.4
Bull Reversal	6.9	2.6	14.0	14.8	–42.3	–12.1	–10.4	–20.6	–14.9

NOTE: * January 1967–December 2020; ** July 1972–December 2018.

1963 sample. However, this result may be distorted by the absence of data for the quality factors, which show poor returns during the bull reversals post-1963.

ALTERNATIVE ASSET PRICING FACTORS

Exhibit 16 reports the return of various alternative asset pricing factors during the different stages of the quant cycle post-1963. Value factors based on E/P and CF/P show roughly the same performance pattern as the HML factor based on the book-to-market ratio, which is not surprising given that they are highly correlated with HML (0.87 and 0.85, respectively). The main difference is that the alternative value factors appear to be a bit less extreme, suffering less during value crashes but also rallying less during bull reversals. The long-term reversal factor, which is also somewhat value-like (0.47 correlation with HML), appears to be less vulnerable not only to value crashes but also to growth rallies. This suggests that it can help diversify a value strategy. However, a major drawback of LTR is that it offers a low premium during the normal regime, which is most prevalent. The short-term reversal factor has a flat return during growth rallies and a large negative return during the (single) value crash in the sample, which is perhaps a surprising result for a factor that is highly adaptive owing to its lookback period of just one month.

We next turn to the return on equity and expected growth factors from the q-factor model of Hou, Xue, and Zhang (2015) and Hou et al. (2021). These factors are quality/momentum-like, with correlations with RMW and WML in the 0.4–0.6 range. This is also clearly reflected in their performance over the cycle. Similar to RMW and WML, the ROE and EG factors have double-digit positive returns during value crashes and bear reversals and double-digit negative returns during bull reversals.

We also consider the post–earnings announcement drift and financing factors from the behavioral asset pricing model of Daniel, Hirsleifer, and Sun (2020). The PEAD factor is momentum-like, with a correlation of 0.48 with WML. Similar to iMom, it is able to strongly mitigate losses during bull reversals, which may be explained by the fact that both factors only have about half of the volatility of WML. However, this does not prevent PEAD from producing double-digit gains that keep up with WML during growth rallies and bear reversals. The FIN factor is an interesting case because it has correlations in the 0.5–0.6 range with HML, RMW, and WML at the same time. Unfortunately, it also seems to combine the vulnerabilities of these factors, with large negative returns during growth rallies like HML and large negative returns during bull reversals like RMW and WML. On the other hand, it does show extremely strong positive returns during bear reversals.

Finally, we consider the CMS factor of Blitz and van Vliet (2018). This factor goes long low-volatility stocks with a high net payout yield and favorable momentum and short high-volatility stocks with a low net payout yield and unfavorable momentum. The CMS factor has a correlation of 0.71 with the VOL factor and correlations of about 0.3 with the HML, RMW, and WML factors. Compared to the VOL factor, the CMS factor is able to prevent losses during growth rallies and value crashes and has even more spectacular performance during bear reversals. However, CMS significantly underperforms VOL during bull reversals, likely because of its momentum exposure.

Altogether, we conclude that the performance of the alternative asset pricing factors over the quant cycle is consistent with their correlations with our base-case factors.

CONCLUSION

In line with previous studies, we find that traditional business cycle indicators do not capture much of the cyclical variation in factor premiums. We argue that this is not surprising if, rather than being a reward for macroeconomic risks, factor premiums are a behavioral phenomenon at heart. Consistent with this notion, we confirm that the Baker and Wurgler (2006) investor sentiment index is more effective at distinguishing between different regimes for factor returns. However, it is still of limited practical use.

Inspired by these findings, we argue that factors essentially follow their own cycle, which can be inferred from factor returns themselves. Following this approach, we identify a cycle consisting of a normal stage that is interrupted by occasional large drawdowns of the value factor, owing to either rallies of growth stocks or crashes of value stocks, which are in turn followed by reversals. The normal stage prevails about two-thirds of the time. Growth rallies or value crashes occur with a frequency of about once every 10 years and typically last about 2 years. During these periods, the value factor underperforms massively, and the low-risk factor tends to underperform. However, momentum is highly effective. These periods are usually followed by a violent reversal, which is characterized by either a crash of the growth stocks that went up strongly in the previous stage or a strong rally of stocks that had poor momentum in the previous stage. We show empirically that this simple three-stage quant cycle is able to capture a huge amount of time variation in factor returns. Exhibit 17 gives a qualitative summary of our main findings.

We conclude that, to understand the cyclical dynamics of factors, investors should recognize that factors follow their own sentiment-driven cycle. Traditional business cycle and sentiment indicators may pick up some of these dynamics, but their practical usefulness is limited. By inferring the quant cycle directly from factor returns, we are able to capture much more time variation. The practical implication for investors is that they should focus their efforts on better understanding the quant cycle as implied by factors themselves, rather than adhering to traditional frameworks that, at best, have a weak relation with actual factor returns. An example of a possible application of the model is that it might help investors formulate a multiyear outlook. For instance, a return to the normal stage appears likely after having gone through a growth rally and subsequent reversal, whereas a growth rally or value crash may become increasingly likely after a prolonged normal period. The model can also be used to evaluate the robustness of new alpha factors by examining their performance across the various stages of the cycle.

Our results also give rise to interesting follow-up research questions. For instance, would it be possible to improve upon the simple 1/N mix of factors to obtain more stable returns over the quant cycle? This is likely to be a challenge because during the growth stage multifactor investors suffer from too much value exposure, whereas during bull reversals they suffer from too little value exposure. Beating 1/N therefore probably requires some factor timing ability—something that is notoriously hard.

EXHIBIT 17

Summary

	Market	Size	Value		Quality		Momentum		Low Risk		
	Mkt-RF	SMB	HML	CMA	RMW	QMJ	WML	iMom	VOL	BAB	1/N
Normal	+	+	+	+	+	+	+	+	+	+	+
Growth Rally	+	0	– –	–	+ +	+ +	+ +	+	–	–	0
Value Crash	– –	–	– –	–	+ +	+ +	+ +	+	–	–	0
Bear Reversal	– –	0	+ +	+ +	+	+	+	+	+ +	+ +	+ +
Bull Reversal	+ +	+ +	+	+	– –	– –	– –	–	–	–	–

Perhaps, however, the quant cycle framework can help provide a fresh perspective on factor timing. The challenge then is to move from identifying the different stages ex post to predicting the current stage ex ante with sufficient accuracy.

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