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TIME-SERIES VARIATION IN FACTOR PREMIA: THE INFLUENCE OF THE BUSINESS CYCLE

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Factor cyclicality can be understood in the context of factor sensitivity to aggregate cash-flow news. Factors exhibit different sensitivities to macroeconomic risk, and this heterogeneity can be exploited to motivate dynamic rotation strategies among established factors: size, value, quality, low volatility and momentum. A timely and realistic identification of business cycle regimes, using leading economic indicators and global risk appetite, can be used to construct long-only factor rotation strategies with information ratios nearly 70% higher than static multifactor strategies. Results are statistically and economically significant across regions and market segments, also after accounting for transaction costs, capacity and turnover.

A revolution has occurred in investment management as both academics and practitioners have recognized that quantitative stock characteristics, such as market capitalization or book-to-market equity are associated with cross-sectional variation in average returns. This has led to a boom in new investment strategies commonly referred to as "smart or strategic beta." Interestingly, the stocks inside portfolios designed to take advantage of these patterns move together, controlling for market movements. Consequently, these patterns represent a dimension of systematic risk different from CAPM beta. We argue that understanding the economic drivers of these new systematic risks brings novel insights as to how to tilt among these factors to help achieve attractive returns.

This insight flows from recognizing that markets are not static but dynamic. Academic research in the 1980s highlighted that aggregate returns are too volatile compared to fundamentals such as aggregate dividends or profitability (Shiller 1981). More than two decades of academic literature have concluded that much of the variation

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in market returns is temporary, reflecting news about future discount rates rather than the permanent news about fundamentals that static models like the CAPM are based on.

Therefore, a potentially useful way to understand what drives variation in smart beta returns comes from disentangling temporary versus permanent movements in the aggregate stock market. Indeed, this view highlights that the sources of risk in factor returns may not be so exotic after all but simply requires decomposing the market return into these two distinct components.

Following Campbell and Vuolteenaho (2004); Campbell, Polk, and Vuolteenaho (2010); Campbell, Giglio, and Polk (2013); and Campbell, Giglio, Polk, and Turley (2018), we exploit the fact that portfolios based on classic quantitative strategies load differentially on the discount-rate news and cash-flow news components of aggregate returns and use this to motivate dynamic factor strategies that generate Information Ratios that are nearly twice as large as static implementations.

Our results can be easily summarized as follows. First, consistent with the aforementioned academic studies, quantitative strategies such as value and small size had relatively large cash-flow betas while other strategies such as low-volatility and quality had relatively low cash-flow betas. Momentum, consistent with the transitory nature of its signal, exhibited a relatively higher cash-flow beta in expansions and lower cash-flow beta in contractions. Importantly, these differences do not simply reflect differences in market beta.

Second, market timing strategies based on timely forecasts of aggregate economic fundamentals can be leveraged through a smart beta lens. Holding the subset of strategies with higher cash-flow beta through the recovery and expansion phases of the business cycle but rotating to the subset of strategies with lower cash-flow beta during the slowdown and contraction phases of the business cycle, outperformed a static allocation to these factors.

1 Factors and factor rotation

1.1 Cross-sectional variation in average returns: A factor view

The use of characteristic-based factor models took hold in academia with the publication of Fama and French (1993), which introduced a three-factor model of stock returns. Their model was designed to capture two well-known patterns in the cross-section of average returns that are not explained by the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965), the size and book-to-market effects.[1] Since then, Fama and French (2015) have expanded their model to capture two patterns related to two additional firm characteristics, investment and profitability.[2]

In financial practice, these findings have led to the introduction of various benchmark indices associated with these characteristics. This so-called "smart-beta" market continues to grow with accelerated innovation in the development of non-traditional offerings. According to Morningstar, smart beta includes strategies with relatively basic style tilts, such as the Russell 1000 Value and Russell 1000 Growth but has also evolved to include a variety of alternatively weighted single-factor and multifactor approaches. In particular, there has recently been an increase in the introduction of multifactor and risk-based investment solutions. These strategies aim to provide attractive risk-adjusted returns for investors by combining two or more of these factors.

1.2 Time-series variation in factor premia

Around the same time that a factor view of markets arose, researchers also documented time-variation in the market risk premium. Campbell and Shiller (1988a, 1988b) and Fama and French (1989) are seminal papers in this literature. As a consequence, it became natural to also investigate time-variation in factor premia. Perhaps the leading example of this line of research is Cohen, Polk, and Vuolteenaho (2003), who documented that the expected return on value-minus growth strategies is relatively high when the spread in book-to-market ratios across the two legs of the strategy (which they dub the "value spread") is relatively wide.[3]

Researchers have also identified momentum and reversal effects in factor returns (Lewellen, 2002, and Teo and Woo, 2004) as well as identified time-variation in factor premia related to share issuance (Greenwood and Hanson, 2012), short interest (Hansen and Sunderam (2014) and factor volatility (Barroso and Santa-Clara, 2015). Given the rise in the popularity of these strategies, researchers have also inquired as to whether time-variation in the profitability of factor strategies can be linked to variation in their popularity among professional investors (Lou and Polk, 2013; Huang, Lou, and Polk, 2018; and Lou, Polk, and Skouras, 2018).

Linking time-variation in factor premia to the business cycle is relatively unexplored, with most studies conducted on a narrow set of factors. Cooper, Mitrache and Priestley (2016) proposed a global macroeconomic risk model for value and momentum, while Ahmerkamp, Grant and Kosowski (2012) studied the predictability of carry and momentum strategies and found strong explanatory power in business cycle indicators. Recent studies have explored the influence of the business cycle across a wider set of equity factors (see Hodges, Hogan, Peterson and Ang (2017) and Varsani and Jain (2018)), providing a descriptive analysis of historical factor performance conditional on economic regimes. However, a comparison of results across these studies reveals differences between the expected cyclical properties and the actual performance of factors in each economic regime. To our knowledge, limited research has been conducted analyzing the influence of the business cycle on factor returns in a single framework. We contribute to the literature by providing a consistent fundamental framework that links the variation in factor performance to the sensitivity to aggregate cash-flow news, across the most commonly established equity factors: size, value, quality, low volatility and momentum.

2 Factors and the business cycle

A key insight since Campbell and Shiller (1988a) is that returns on the market portfolio are comprised of two components. The market may drop in value because investors receive bad news about future cash flows, but it may also drop because, all else equal, investors increase the discount rate that they apply to these expected cash flows going forward. This distinction naturally follows from recognizing that the market risk premium varies through time.

The Campbell-Shiller log-linear present-value model facilitates that distinction. In particular, following Campbell and Shiller (1988a), Campbell (1991) shows how unexpected log returns on an asset may be decomposed written as follows:

$$\begin{aligned} r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \\ &\quad - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \Delta r_{t+1+j} \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned} \tag{1}$$

$N_{CF,t+1}$ reflects news about future cash flows, $N_{DR,t+1}$ reflects news about future expected returns, and ρ is a discount coefficient determined by the average log dividend yield.[4] Note that this decomposition is simply an accounting identity and not a behavioral model, taking no stance on whether variation in expected returns is rational or irrational.[5]

Differentiation between these two components of the market return is important as a large body of research starting with Shiller (1981) has shown that most of the variation in market valuations is from the latter.

Researchers have exploited this decomposition to show that different types of stocks load differently on these two components of market risk. Indeed, Campbell and Vuolteenaho (2004) propose a model where investors care more about permanent cash flow-driven movements than about temporary discount rate-driven movements in the aggregate stock market. In their model, the required return on a stock is determined not by its overall beta with the market, but by two separate betas, one with permanent cash-flow shocks to the market, and the other with temporary shocks to market discount rates.

This theoretical distinction has empirical traction as Campbell and Vuolteenaho (2004) show that small stocks and value stocks had higher cash-flow betas than their large and growth counterparts. Recent papers by Campbell, Polk, and Vuolteenaho (2010) and Campbell, Giglio, Polk, and Turley (2018) document rich heterogeneity in terms of exposure to aggregate cash-flow news linked to fundamental firm characteristics often associated with smart beta strategies, such as profitability and leverage.

This heterogeneity may be important in devising factor timing strategies. In particular, signals which anticipate the evolution of the business cycle can be viewed through a factor lens. If a signal is positive about future market fundamentals, then tilting towards strategies which are known to have relatively high cash-flow betas is relatively attractive. Alternatively, if a signal is negative about future market fundamentals, then tilting towards strategies which are known to have relatively low cash-flow betas is the more attractive option.

3 Data and summary statistics

When vetting the ability of a particular strategy to generate additional returns over time, one can examine a few key attributes such as pervasiveness, persistence, intuitiveness, robustness, and investability. Our analysis studies the FTSE Russell Factor Indexes, which reference five equity factors supported by academic research, where each factor has a significant amount of theoretical research proposing explanations justifying the observed predictability. These indices represent common factor characteristics supported across different geographies and time periods, covering the following universes: U.S. Large Cap, U.S. Small Cap, Developed ex-U.S. and Emerging Markets across the following factors—Value, Quality, Momentum, Low Volatility, and Size. For the purpose of this paper we use the Russell 1000 universe and the factor definitions set forth in Exhibit 1.[6] Exhibit 2 provides some key summary statistics.

Consistent with a large body of academic research beginning at least in the 1990s, these indices have outperformed the market since inception, on a risk-adjusted basis.

Exhibit 3 reports the correlation matrix of factor returns. As the data shows, the excess returns of the factors are not extremely correlated, suggesting the possibility of useful diversification benefits when used in combination, justifying the relatively recent move to static multifactor implementations. Our analysis emphasizes that exploiting the time variation in the expected return components of these realized returns can be beneficial, and add incremental returns over a static multifactor implementation.

Exhibit 1: Factor definitions.

Factor	Description	FTSE Russell factor definition	FTSE Russell Factor Index
Value	Stocks that appear cheap tend to perform better than stocks that appear expensive.	Equally weighted composite of cash-flow yield, earnings yield and price-to-sales ratio	Russell 1000 Value Factor Index
Quality	Higher-quality companies tend to perform better than lower-quality companies.	Equally weighted composite of profitability (return on assets, change in asset turnover, accruals) and leverage ratio	Russell 1000 Quality Factor Index
Size	Smaller companies tend to perform better than larger companies.	Inverse of full market capitalization index weights	Russell 1000 Size Factor Index
Low Volatility	Stocks that exhibit low volatility tend to perform better than stocks with higher volatility on a risk-adjusted basis.	Standard deviation of five years of weekly total returns	Russell 1000 Volatility Factor Index
Momentum	Stocks that rise or fall in price tend to continue rising or falling in price.	Cumulative 11-month return (last 12 months excluding the most recent month)	Russell 1000 Momentum Factor Index

Source: FTSE Russell.

Exhibit 2: Single-factor performance characteristics.

	Return	Standard deviation	Excess return	Sharpe ratio	Information ratio	Max drawdown	Skewness
Russell 1000 Low Volatility Factor Index	11.67	12.87	−0.03	0.54	−0.01	−46.90	−0.58
Russell 1000 Momentum Factor Index	12.06	15.00	0.36	0.49	0.17	−49.13	−0.62
Russell 1000 Quality Factor Index	12.09	14.91	0.38	0.49	0.13	−47.13	−0.59
Russell 1000 Size Factor Index	13.22	16.57	1.52	0.51	0.26	−53.00	−0.79
Russell 1000 Value Factor Index	12.34	14.71	0.64	0.51	0.15	−54.35	−0.72
Russell 1000 TR USD	11.70	14.81	0.00	0.47	–	−51.13	−0.67

Source: FTSE Russell 6/30/1980 to 9/30/2018. Russell 1000 Factor Indexes inception date: September 30, 2015. The returns of the Index prior to 9/30/15 represent hypothetical pre-inception index performance to illustrate how the Indices may have performed had they been in existence for the time period prior to 9/30/15. Performance, actual or hypothetical, is not a guarantee future results. An investment cannot be made in an index. Please see Exhibit A5 for time periods of Maximum Drawdown and Endnotes for definitions.

Exhibit 3: Factor excess return correlations (July 1980–September 2018).

	Size	Value	Low Vol.	Quality	Momentum
Size	1				
Value	0.32	1			
Low Vol.	−0.42	0.30	1		
Quality	−0.27	−0.55	−0.06	1	
Momentum	−0.05	−0.44	−0.15	0.29	1

Source: FTSE Russell and FactSet as of 9/30/18.

Further examination of historical returns on these factors shows they have exhibited pronounced cyclicality. For example, in some years size consistently outpaced the market, whereas in other years, low volatility was the best performing factor. This paper analyzes *ex ante* investment strategies that are designed to take advantage of predictable aspects of this apparent cyclicality. In particular, we motivate our work using the cash-flow news series introduced above and described in detail in the Appendix. Exhibit 4 plots smoothed versions of $N_{CF,t+1}$ and $N_{DR,t+1}$. As the plot shows, $N_{CF,t+1}$ clearly better reflects movement in underlying fundamentals relative to $N_{DR,t+1}$, given even a casual understanding of the history of news about the underlying business cycle during this period. For example, the 1920s and 1930s were characterized by negative return contribution from cash-flow news, driven by the Great Depression. Similarly, negative cash-flow news contributions are registered across the major economic downturns of the following decades.

4 Empirical results

4.1 Factor exposures to cash-flow news

We first document intuitive differences in the cash-flow betas of the Russell indices by regressing the monthly returns of each factor on the aforementioned cash-flow news variable. Following Scholes and Williams (1977) and Dimson (1979), we include lags of cash-flow news. Specifically, we estimate regressions of the form

$$R_{p,t+1} = a + \sum_{k=0}^{2} \beta_p N_{CF,t+1-k} + \epsilon_{p,t+1} \qquad (2)$$

Exhibit 4: Smoothed components of aggregate returns (July 1926–June 2018).

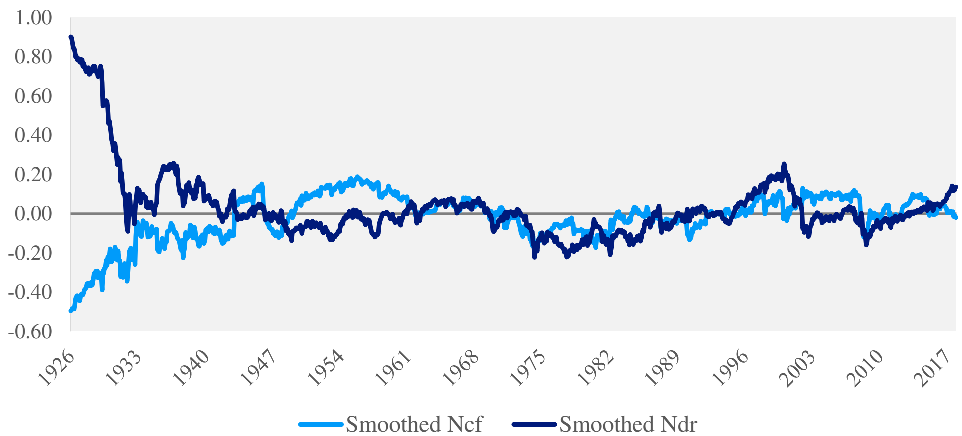


Exhibit 5: Single-factor exposure to aggregated cash-flow news (July 1980–June 2018).

	Constant	Cash-flow news sensitivity	R^2
Russell 1000	0.01	0.97	0.19
	(5.28)	(6.98)	
Comprehensive	0.01	0.91	0.16
Factor Index	(6.75)	(6.79)	
Low volatility	0.01	0.75	0.15
	(5.83)	(6.06)	
Quality	0.01	0.94	0.18
	(5.41)	(6.69)	
Momentum	0.01	0.99	0.17
	(5.28)	(6.71)	
Value	0.01	0.99	0.17
	(5.55)	(7.14)	
Size	0.01	1.16	0.18
	(5.37)	(7.45)	

Source: FTSE Russell as of 6/30/18. We report t-statistics in parentheses. Sample time-period dictated by data availability for factor indices and cash-flow news series.

and report the sum of β_p along with the associated t statistic.[7] For comparison, we include the Russell 1000 and the Russell 1000 Comprehensive Factor Index, which represents an equally weighted static exposure to the five factors.[8] Exhibit 5 documents that the factors we study have differential exposures to aggregate cash-flow news. In particular, size, and to some degree value had sensitivities that are higher than the Russell 1000 Index, and clearly higher than a static multifactor approach. Momentum also exhibited relatively higher cash-flow sensitivity. However, as it will be illustrated shortly, its relative sensitivity varies substantially across the stages of the business cycle, in line with the transitory nature of its signal definition. In stark contrast, quality and particularly low volatility had relatively low cash-flow sensitivities compared to the Russell 1000. These results are consistent with previous academic research. Next, we utilize a forward-looking framework to identify the different stages of the business cycle, and attempt to exploit these differential factor exposures by mapping a different factor portfolio to each macro regime.

4.2 Forecasting fundamental news

We classify the different stages of the business cycle based on the level and change in economic growth, and define the following four regimes:

Recovery: growth below trend and accelerating

Expansion: growth above trend and accelerating

Slowdown: growth above trend and decelerating

Contraction: growth below trend and decelerating

Exhibit 6a provides a *stylized* plot of the business cycle regimes we aim to measure. In order to forecast the evolution of the economic cycle along these regimes, we construct a macro regimes framework which combines the interaction between a US leading economic indicator ("US LEI") and a global risk appetite cycle indicator ("GRACI") using the following rules

$$Recovery_{t+1}: US\,LEI_t < LT\,LEI\,trend_t \;\&\; GRACI_t \geq MA(GRACI)_t$$

$$Expansion_{t+1}: US\,LEI_t \geq LT\,LEI\,trend_t \;\&\; GRACI_t \geq MA(GRACI)_t$$

$$Slowdown_{t+1}: US\,LEI_t \geq LT\,LEI\,trend_t \;\&\; GRACI_t < MA(GRACI)_t$$

$$Contraction_{t+1}: US\,LEI_t < LT\,LEI\,trend_t \;\&\; GRACI_t < MA(GRACI)_t$$

where $LT\,LEI\,trend_t$ stands for long-term trend in the US LEI at time t, and $MA(GRACI)_t$ stands for short-term moving average in the GRACI at

Exhibit 6a: Stylized business cycle regimes.

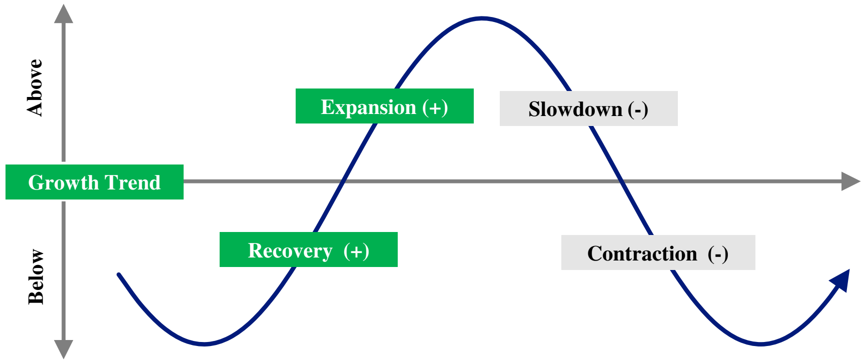


Exhibit 6b:

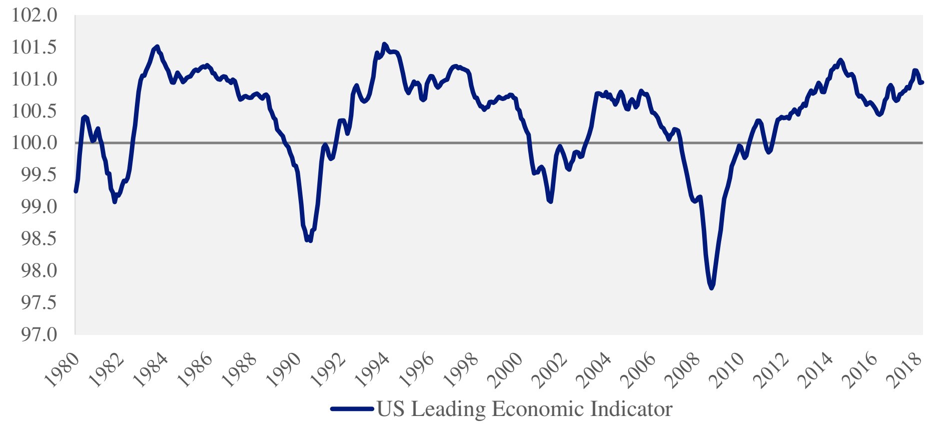
GRACI Accelerating	**Recovery**	**Expansion**
GRACI Decelerating	**Contraction**	**Slowdown**
	US LEI below Long-Term Trend	US LEI above Long-Term Trend

time t. In other words, the forecasting rule of the four regimes is driven by whether (a) the US LEI is above or below its long-term trend and (b) whether GRACI is above or below its short-term moving average (i.e. accelerating or decelerating). These rules are also summarized in Exhibit 6b, where the four macro regimes are mapped to their model-based forecast rules.

In other words, we first construct a US leading economic indicator to determine whether growth is likely to be above or below trend, using the same panel of variables selected by the OECD for the U.S. composite leading indicator.[9] However, to eliminate well-known issues of look-ahead bias in statistical filtering techniques, we use a simple z-scoring procedure to de-trend, normalize and smooth each variable. In addition, we use first vintage economic data as far back as possible, to ensure a realistic use of information available at the time[10]. Finally, these normalized variables are aggregated with equal weights into a composite index (Exhibit 7a).

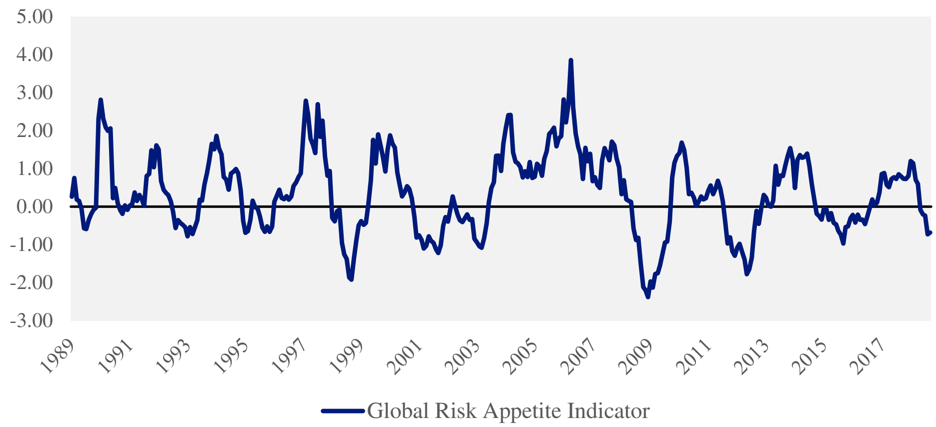
Second, we estimate the future directional change in economic growth from cyclical fluctuations in global risk appetite. As is well known and consistent with our return decomposition, financial markets contain information about future economic activity, as market participants discount information affecting future fundamentals in real time. Notably, asset prices can reflect a broader set of fundamental news, such as changes in monetary conditions, fiscal policy announcements, corporate news, global financial shocks, etc. While these fundamental drivers are reflected in economic activity with a lag, market participants continuously revisit their economic outlook and adjust their propensity to take risk accordingly. Indeed, in almost all models, market premia and risk aversion are tied to the amount of risk in the economy, and both these objects have been

Exhibit 7a: U.S. leading economic indicators ("LEI"), (Trend = 100).



Source: Bloomberg L.P., OECD, Federal Reserve, Bureau of Economic Analysis 6/30/1980 to 9/30/2018. Sample time-period dictated by data availability.

Exhibit 7b: Global risk appetite indicator ("GRACI").



Source: Bloomberg L.P., FTSE Russell, MSCI Inc., JPMorgan 12/31/1988 to 9/30/2018. Sample time-period dictated by data availability.

shown to be negatively correlated with business conditions (Campbell and Cochrane, 1999, for the former and Black, 1976, and Christie 1982 for the latter).

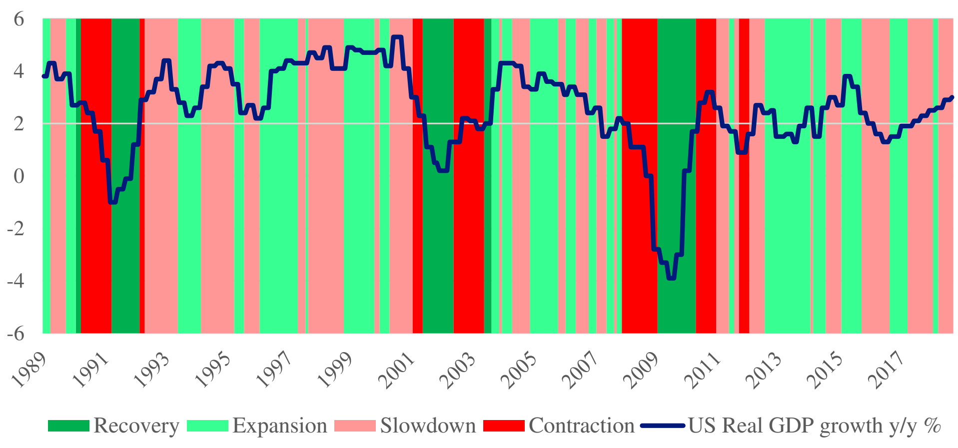
Thus, cyclical fluctuations in global risk premia can be used to forecast subsequent variation in economic risk and future risk premia. Polk, Thompson, and Vuolteenaho (2006) show how cross-sectional techniques can be used to forecast time-variation in the market risk premium. Similarly, Kumar and Persaud (2002) use cross-sectional regressions of risks and returns to extract investor behavior and risk appetite, emphasizing the increasing importance of global financial markets, in addition to domestic fundamentals, given the exponential increase in trade linkages, cross-border capital flows, and portfolio contagion channels. In a related fashion, we define global risk appetite as the incremental return received by investors for taking an incremental unit of risk in global financial markets over the past year, and construct it using country-level equity, government bond and corporate bond indices across both developed and emerging markets (Exhibit 7b). Consistent with the literature, this indicator has a strong and statistically significant correlation with several proxies of the global business cycle (see for example de Longis and Ellis (2019))[11]. Our US LEI and GRACI indicators are illustrated in Exhibit 7. Details of their construction methodology are reported in Section II of the Appendix.

As mentioned above, our final composite business cycle model combines the U.S. leading economic indicator and global risk appetite to forecast the four stages of the business cycle, as summarized in Exhibit 6b. The output of our model is illustrated in Exhibit 8, where our estimated macro regimes are plotted through time, and visually compared to realized GDP growth. Exhibit 8 is suggestive of the predictive content of our model-based regime classification versus directional changes in realized GDP growth.

4.3 *A regime-based view: Cash-flow sensitivities and relative returns*

As a final step, we construct four distinct factor portfolios, one for each business cycle regime, based on our knowledge of cash-flow sensitivities of these factors, previously shown in Exhibit 5. Consistent with the literature, we expect the performance of size and value relative to the market to be pro-cyclical, while quality and low volatility to be counter-cyclical. Unlike these four factors, the momentum factor cannot be linked to persistent fundamental characteristics such as leverage or profitability. The momentum premium is based on the behavioral premise of continuation of recent prices trends, and its signal is relatively transitory. Therefore, with respect to its cyclicality, we expect momentum to outperform in the late-stage of a cyclical upturn (i.e. expansion) and late-stage of a downturn (i.e. contraction) and, conversely, to underperform in the phases following cyclical turning points (i.e. recovery and slowdown), where relative price trends are likely to change. If correct, this behavioral premise should also have implications for the exposure of momentum to cash-flow news. We measure these sensitivities relative to the Russell 1000 to confirm that these patterns do not just reflect broader patterns in the market. As the business cycle regime can change from one month to the next, and as momentum is a relatively transitory

Exhibit 8: Model-predicted business cycle regimes versus realized GDP growth.



Source: Business cycle regimes are computed by the authors, based on the composite business cycle regime model outlined in Section 2 of the Appendix, using a combination of US leading economic indicators and global risk appetite indicator. US GDP time series is sourced from the Bureau of Economic 12/31/1988 to 9/30/2018. US GDP data do not contribute to the calculation of the regimes, and they are illustrated for reference purposes only. Sample time-period dictated by data availability.

Exhibit 9: Momentum factor's conditional cash-flow sensitivity (January 1989–June 2018).

	Constant	Cash-flow news sensitivity	R^2
Unconditional	0.00	−0.01	0.00
($N = 354$)	(1.17)	(−0.48)	
Recovery	0.00	−0.04	−0.02
($N = 43$)	(0.35)	(−0.54)	
Expansion	0.00	0.05	0.00
($N = 124$)	(1.04)	(1.06)	
Slowdown	0.00	0.03	0.00
($N = 131$)	(0.51)	(0.74)	
Contraction	0.00	−0.09	0.07
($N = 56$)	(0.04)	(−2.24)	

Source: FTSE Russell as of 6/30/18. We report t-statistics in parentheses. Sample time-period dictated by data availability.

signal, we only measure contemporaneous sensitivities. Exhibit 9 reports that the momentum factor exhibited clear variation in relative cash-flow sensitivity across the four regimes. Specifically, the Russell 1000 momentum strategy had a relatively high cash-flow sensitivity (0.05) during the Expansion regime and a relatively low cash-flow sensitivity (−0.09) during the Contraction regime. The difference with the respective sensitivities of the Recovery and Slowdown regime are statistically significant, and consistent with the expectation of relative outperformance of the momentum factor in late-stage regimes versus early-stage regimes.

With these facts in hand, we examine combinations of these five factors based on the regime/tilt matrix described in Exhibit 10. We use these tilts as characteristic weights in the standard FTSE Russell methodology (FTSE Russell 2017).

The FTSE Russell approach utilizes a Tilt-Tilt ('Bottom-up' portfolio construction) with sequential or 'multiplicative' tilts away from market cap weighting on each factor, with the outcome independent of ordering. This creates approximately the same exposures of single-factor indexes, without the dilutive effects of other methods. The magnitude of tilt is determined by the business cycle indicator and adjusted for implementation concerns such as liquidity, capacity, diversification and turnover.[12] Exhibit 10 highlights the tilts given the regimes described above. In this matrix, a '1' indicates that we multiply a company's market cap by the factor score a single time, and a '2' indicates that we multiply by the factor score twice. A '0' indicates that the factor is not targeted. For comparison, we include both the Russell 1000

Exhibit 10: Factor tilts through the business cycle.

Factor Tilts for Given Regime					
	Low Volatility	Size	Value	Momentum	Quality
Recovery	0	2	2	0	0
Expansion	0	1	1	2	0
Slowdown	2	0	0	0	2
Contraction	2	0	0	2	2
Factor Tilts for Other Russell Indices					
Russell 1000	0	0	0	0	0
R1 Comprehensive Factor	1	1	1	1	1

Exhibit 11: Cash-flow sensitivity by regime portfolio (July 1980–June 2018).

	Constant	Cash-flow news sensitivity	R^2
Recovery portfolio (R)	0.01	1.09	0.16
	(5.90)	(6.95)	
Expansion portfolio (E)	0.01	1.09	0.18
	(5.97)	(7.46)	
Slowdown portfolio (S)	0.01	0.74	0.15
	(6.32)	(6.03)	
Contraction portfolio (C)	0.01	0.82	0.14
	(5.94)	(6.12)	
$0.5 * (R + E) -0.5 * (S + C)$	0.00	0.31	0.03
	(1.39)	(3.81)	

Source: FTSE Russell as of 6/30/18. We report t-statistics in parentheses.

Exhibit 12: Composite portfolio's cash-flow sensitivity (January 1989–June 2018).

	Constant	Cash-flow news sensitivity	R^2
Unconditional ($N = 354$)	0.00	0.19	0.04
	(1.14)	(3.83)	
Recovery or expansion ($N = 167$)	0.00	0.10	0.00
	(2.49)	(1.14)	
Slowdown or contraction ($N = 187$)	0.00	0.23	0.07
	(−0.67)	(3.78)	

Source: FTSE Russell as of 6/30/18. We report t-statistics in parentheses. Portfolio calculations $= 0.5*(R+E)-0.5*(S+C)$.

Index, which carries a '0' tilt to each factor, and the Russell 1000 Comprehensive Factor Index, which has a static single tilt to each factor.

Exhibit 11 documents that the resulting regime portfolios have the predicted exposure to cash-flow news. The Recovery and Expansion portfolios are designed to load on the business cycle and both have a total cash-flow sensitivity of 1.09. In stark contrast, the Slowdown and Contraction portfolios are designed to load less on the business cycle and had total cash-flow sensitivities of 0.74 and 0.82, respectively. For a formal statistical test, we measure the cash-flow sensitivity of a composite portfolio that is long an equal-weight average of the Recovery and Expansion regime portfolios and short an equal-weight average of the Slowdown and Contraction regime portfolios. The total cash-flow sensitivity of that portfolio is 0.31 and statistically significant.

Finally, in Exhibit 12, we document how the sensitivity of our composite portfolio varies across the two main types of regimes (Recovery and Expansion or Slowdown and Contraction). In the former, we want a portfolio that has relatively positive cash-flow news sensitivity. In the latter, we want a portfolio that has relatively negative cash-flow sensitivity. The exhibit confirms this is the case, as during the Recovery and Expansion regimes, the recovery and expansion portfolio had a cash-flow sensitivity that is 0.10 higher than the corresponding estimate of the slowdown and contraction portfolio. Conversely, during the Slowdown and Contraction regimes, the slowdown and contraction portfolio had a cash-flow sensitivity that is 0.23 lower than the corresponding estimate of the recovery and expansion portfolio. Thus, the difference across these two quite different components of the business cycle is 0.33 and highly statistically significant.

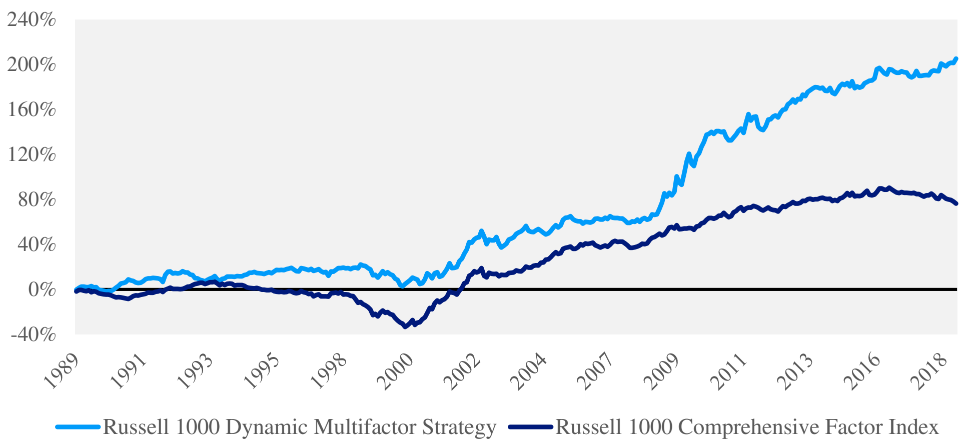
Exhibit 13 puts this all together, reporting the excess returns and associated information ratios provided by the dynamic multifactor model. The dynamic implementation strongly outperformed both the Russell 1000 Index and the static multifactor implementation of the Russell Comprehensive Factor Index, with average annual excess returns of about 4.5% and 2% over these two benchmarks. Furthermore, given an average

Exhibit 13a: Mean returns (before transaction costs) and *t*-statistic (January 1989–September 2018).

	Mean monthly return	Mean monthly excess return over Russell 1000 Index	Mean monthly excess return over R1000 comprehensive Factor Index
Russell 1000	0.94%		
	(4.32)		
Russell 1000 Comp.	1.11%	0.17%	
Factor Index	(5.43)	(2.11)	
Russell 1000 Dynamic	1.26%	0.33%	0.16%
Multifactor Strategy	(6.15)	(3.71)	(1.97)

Source: FTSE Russell and Bloomberg L.P. as of 9/30/18. Mean monthly returns, non-annualized. We report *t*-statistics in parentheses. Results do not include transaction costs. Sample dictated by data availability. All information presented prior to Sept. 28, 2015 for the Russell 1000 Comprehensive Factor Index, and all information prior to October 13, 2017 for the Russell 1000 Invesco MultiFactor Index is back-tested. Back-tested performance is not actual performance but is hypothetical. Although back-tested data may be prepared with the benefit of hindsight, these calculations are based on the same methodology that was in effect when the index was officially launched. Index returns do not reflect payment of any sales charges or fees. Performance, actual or hypothetical, is not a guarantee future results. An investment cannot be made in an index.

Exhibit 13b: Cumulative excess returns over Russell 1000 Index (January 1989–September 2018).



Source: FTSE Russell and Bloomberg L.P. as of 9/30/18. Results do not include transaction costs.

one-way annual turnover of 150% and estimated transaction costs of 7–10 bps per 100% turnover, these results are economically significant also after transaction costs.

Finally, we apply the same model-based macro framework and factor tilts to document dynamic factor rotation strategies for the Russell 2000, FTSE Developed Markets ex-USA and FTSE

Exhibit 13c: Dynamic multifactor strategy performance characteristics (January 1989–September 2018).

	Returns	Standard deviation	Excess returns	Sharpe ratio	Information ratio	Max drawdown	Skewness
Russell 1000 Dynamic Multifactor Strategy	15.23%	13.45%	4.52%	0.92	0.78	−43.25%	−0.29
Russell 1000 Comprehensive Factor Index	13.12%	13.33%	2.41%	0.77	0.46	−45.53%	−0.71
Russell 1000 Index	10.71%	14.20%	–	0.55	0.00	−51.13%	−0.65

Source: FTSE Russell and Bloomberg as of 9/30/18. Average annual returns. Results do not include transaction costs. Sample dictated by data availability. Please see Exhibit A5 for time periods of Maximum Drawdown and Endnotes for definitions.

Emerging Markets benchmarks (details reported in the Appendix). Results are broadly consistent and statistically significant, providing additional support to the robustness of this framework, and its practical relevance to global investors across regions and market segments.

5 Conclusions

Portfolios based on quantitative characteristics such as value, momentum, and quality have historically generated relatively high average returns and represent a new dimension of systematic risk. We argue that understanding the economic drivers of these new systematic risks brings novel insights as to how to time these factor bets. In particular, market timing strategies based on more timely forecasts of aggregate fundamentals can be leveraged through a smart beta lens, as these smart beta portfolios differentially load on aggregate cash-flow news. Dynamic factor strategies exploiting this insight generated information ratios nearly 70% higher than static implementations, while generating excess returns of about 4.5% per annum versus their benchmark index over the past 30 years. Results are statistically significant after accounting for transaction costs, capacity and turnover, and they are robust across market cap segments and geographies.

Appendix

I Derivation of cash-flow news series

Campbell, Giglio, Polk, and Turley's (2018) (CGPT) VAR specification contains six state variables measured monthly over the period from June 1926 to June 2018. The first variable in the VAR is based on the usual proxy for aggregate wealth and is the log real return on the market, rM, the difference between the log return on the Center for Research in Security Prices (CRSP) value-weighted stock index and the log return on the Consumer Price Index. The second variable is expected market variance (EVAR), capturing the market return variance of market returns, σ^2, conditional on information available at time t, so that innovations to this variable can be mapped to volatility news. To construct EVAR, CGPT first create a series of within-month realized variance of daily returns, RVAR. CGPT then run a regression of RVAR on its lagged value as well as the lagged values of the other five state variables, creating a series of predicted values for RVAR, which becomes the variable EVAR. The third variable is the log price-to-smoothed-earnings ratio (PE).[14] The fourth is the term yield spread (TERM), the difference between the log yield on the 10-year U.S. Constant Maturity Bond and the log yield on the 3-Month U.S. Treasury Bill. The fifth state

Exhibit A1: CGPT estimation of the monthly VAR.

	Constant	rM_{t-1}	$EVAR_{t-1}$	PE_{t-1}	$TERM_{t-1}$	DEF_{t-1}	VS_{t-1}
rM	0.0562	0.0892	0.1978	−0.0112	0.0019	−0.0003	−0.0130
	2.85	2.72	0.25	−2.10	1.19	−0.06	−2.12
EVAR	−0.0040	−0.0026	0.5036	0.0010	−0.0001	0.0015	0.0005
	−5.65	−2.16	17.33	5.41	−2.07	8.82	2.16
PE	0.0198	0.5005	0.6301	0.9930	0.0012	−0.0031	−0.0006
	1.70	25.75	1.32	316.10	1.26	−1.13	−0.17
TERM	−0.0436	−0.0477	2.6513	0.0213	0.9469	0.0676	−0.0120
	−0.36	−0.24	0.54	0.66	97.25	2.37	−0.32
DEF	0.0632	−0.7666	5.6451	−0.0174	−0.0049	0.9513	0.0227
	1.30	−9.50	2.86	−1.34	−1.25	82.27	1.51
VS	0.0142	0.1188	0.1204	0.0067	−0.0021	0.0154	0.9708
	0.71	3.57	0.15	1.24	−1.27	3.22	156.05

variable is the default spread (DEF), defined as the difference between the log yield on Moody's BAA and AAA bonds. The final variable is the small-stock value spread (VS). Exhibit A1 presents CGPT's estimation of the monthly VAR. Standard errors include a Newey-West adjustment based on 12 lags.

In particular, CGPT estimate a heteroskedastic VAR,

$$x_{t+1} = \bar{x} + \Gamma(x_t - \bar{x}) + \sigma_t u_{t+1}, \qquad (3)$$

where x_{t+1} is the nx1 vector of state variables with rM as the first element, σ^2_{t+1} as the second element, $\bar{x}$ and Γ as parameters, and u_{t+1} a vector of shocks with constant variance-covariance matrix, Σ, where element 11 is equal to 1. CGPT define an $n \times 1$ vector e_1 with zero elements except for a unit first element. Their structure implies

$$N_{DR,t+1} = e_1' \rho\Gamma(I - \rho\Gamma)^{-1}\sigma_t u_{t+1} \qquad (4)$$

$$N_{CF,t+1} = (e_1' + e_1'\rho\Gamma(I - \rho\Gamma)^{-1})\sigma_t u_{t+1} \qquad (5)$$

CGPT follow previous academic research and set ρ to an annualized value of 0.95.

II US leading economic indicator and global risk appetite indicator

Our US leading economic indicator ("LEI") is an equally weighted average of several economic variables, where each variable is de-trended, normalized and smoothed with a simple z-scoring procedure $z = \frac{x-\mu}{\sigma}$, where x is the economic variable, μ is its long-term moving average and σ its standard deviation. Finally, z is smoothed via a shorter-term moving average. The de-trending procedure is calibrated to the typical length of a business cycle, normally between 7-10 years.

Our global risk appetite cycle indicator ("GRACI") represents the incremental return received by investors over a one-year look-back window (i.e. between t and $t - x$) per incremental unit of risk, and it is computed as the slope β of a cross-sectional regression between excess returns over cash, r_j, and their volatility σ_j, using a large set of country-level total return indices (j) across equity and fixed income markets, from the perspective of a US dollar based investor:

$$r_{t|t-x,j} = \alpha + \beta\sigma_{t-x,j} + \varepsilon_{tj}. \qquad (6)$$

III Dynamic multifactor strategy: Extension to other market segments and regions

Russell 2000 dynamic multifactor strategy

We apply the same methodology, factor definitions and macro regimes used for the Russell 1000 to the universe of stocks in the Russell 2000 index. Therefore, we use the same macro regimes derived from the intersection of the US leading economic indicator and global risk appetite indicator, illustrated in Exhibit 7a and Exhibit 7b, and the factor tilts illustrated in Exhibit 10, to dynamically rotate among the same five factors within the Russell 2000 index. Results are reported in Exhibit A2. The dynamic implementation strongly outperformed both the Russell 2000 Index and the static multifactor implementation of the Russell 2000 Comprehensive Factor

Exhibit A2a: Mean returns (before transaction costs) and *t*-statistic (January 1989–September 2018).

	Mean monthly return	Mean monthly excess return over Russell 2000 Index	Mean monthly excess return over R2000 comprehensive Factor Index
Russell 2000	0.95%		
	(3.39)		
Russell 2000 Comprehensive Factor Index	1.14%	0.19%	
	(4.78)	(2.02)	
Russell 2000 Dynamic Multifactor Strategy	1.27%	0.32%	0.13%
	(5.02)	(3.30)	(1.90)

Source: FTSE Russell and Bloomberg L.P. as of 9/30/18. Mean monthly returns, non-annualized. We report *t*-statistics in parentheses. Results do not include transaction costs. Sample dictated by data availability. All information presented prior to June 22, 2016 for the Russell 2000 Comprehensive Factor Index, and all information prior to October 13, 2017 for the Russell 2000 Invesco MultiFactor Index is back-tested. Back-tested performance is not actual performance but is hypothetical. Although back-tested data may be prepared with the benefit of hindsight, these calculations are based on the same methodology that was in effect when the index was officially launched. Index returns do not reflect payment of any sales charges or fees. Performance, actual or hypothetical, is not a guarantee future results. An investment cannot be made in an index.

Exhibit A2b: Russell 2000 Dynamic Multifactor Strategy Performance Statistics (January 1989–September 2018).

	Returns	Standard deviation	Excess returns	Sharpe ratio	Information ratio	Max drawdown	Skewness
Russell 2000 Dynamic Multifactor Strategy	14.82%	16.59%	4.69%	0.72	0.73	−48.42%	−0.26
Russell 2000 Comprehensive Index	13.20%	15.62%	3.08%	0.66	0.49	−50.44%	−0.60
Russell 2000 Index	10.13%	18.32%	0.00%	0.39	0.00	−52.89%	−0.53

Source: FTSE Russell and Bloomberg as of 9/30/18. Average annual returns. Results do not include transaction costs. Sample dictated by data availability. Please see Exhibit A5 for time periods of Maximum Drawdown and Endnotes for definitions.

Index, with average annual excess returns of about 4.7% and 1.7% over these two benchmarks. Furthermore, given an average one-way annual turnover of 150% and estimated transaction costs of 30–60 bps per 100% turnover, these results are economically significant also after transaction costs.

FTSE developed markets ex-USA and FTSE emerging markets dynamic multifactor strategies

Using the same factor definitions (Exhibit 1) and factor tilts (Exhibit 10), we investigate the efficacy of our macro regime framework for the FTSE Developed Markets ex-USA and

Exhibit A3a: Mean monthly returns (before transaction costs) and t-statistics (August 1997–September 2018).

	Mean return	Mean excess return over FTSE DM ex USA Index	Mean excess return over FTSE DM ex USA comprehensive Factor Index
FTSE DM ex USA	0.54%		
	(1.81)		
FTSE DM ex USA	0.85%	0.31%	
Static Multifactor Portfolio	(3.31)	(3.33)	
FTSE DM ex USA Dynamic	1.05%	0.50%	0.20%
Multifactor Strategy	(3.81)	(4.51)	(2.04)

Source: Source: FTSE Russell and Bloomberg L.P. as of 9/30/18. Mean monthly returns, non-annualized. We report t-statistics in parentheses. Results do not include transaction costs. Sample dictated by data availability. The FTSE DM ex USA Static Multifactor portfolio uses a common methodology to achieve controlled exposure to five target factors, whilst considering levels of diversification and capacity. All information presented prior to Jun. 30, 2000 for the FTSE Developed ex US Index and the FTSE Static Multifactor portfolio is back-tested. Back-tested performance is not actual performance, but is hypothetical. Although back-tested data may be prepared with the benefit of hindsight, these calculations are based on the same methodology that was in effect when the index was officially launched. Index returns do not reflect payment of any sales charges or fees. Performance, actual or hypothetical, is not a guarantee future results. An investment cannot be made in an index.

Exhibit A3b: FTSE DM ex-USA dynamic Multifactor strategy performance statistics (August 1997–September 2018).

	Return	Standard deviation	Excess return	Sharpe ratio	Information ratio	Max drawdown	Skewness
FTSE DM ex USA Dynamic Multifactor Strategy	12.06%	15.17%	6.81%	0.67	1.10	−48.93%	−0.10
FTSE DM ex USA Static Multifactor Portfolio	9.61%	14.21%	4.36%	0.54	0.85	−50.47%	−0.74
FTSE DM ex USA Index	5.25%	16.56%	–	0.20	0.00	−56.32%	−0.66

Source: FTSE Russell and Bloomberg as of 9/30/18. Average annual returns. Results do not include transaction costs. Sample dictated by data availability. Please see Exhibit A5 for time periods of Maximum Drawdown and Endnotes for definitions.

FTSE Emerging Markets benchmarks. In order to deploy our macro regime methodology, we replace the US leading economic indicator with equivalent leading economic indicators for each region. Given the limited availability of first vintage economic data outside the US, both in terms breadth and history, we rely on a single indicator across countries, using country-level Markit PMI Manufacturing new orders surveys, weighted by GDP, to create a Developed Markets ex-USA and an Emerging Markets composite leading economic indicator.[13] Finally, we combine each composite leading indicator with the same global risk appetite indicator described above to define the four regimes of each regional business cycle, as per the same methodology outlined in

Exhibit A4a: Mean monthly returns (before transaction costs) and *t*-statistics (January 2005–September 2018).

	Mean return	Mean excess return over FTSE EM Index	Mean excess return over FTSE EM comprehensive Factor Index
FTSE EM	0.84%		
	(1.72)		
FTSE EM Static	1.07%	0.23%	
Multifactor Portfolio	(2.41)	(2.45)	
FTSE EM Dynamic	1.26%	0.42%	0.19%
Multifactor Strategy	(2.70)	(3.55)	(1.63)

Source: FTSE Russell and Bloomberg L.P. as of 9/30/18. Mean monthly returns, non-annualized. We report *t*-statistics in parentheses. Results do not include transaction costs. Sample dictated by data availability. The FTSE EM Static Multifactor portfolio uses a common methodology to achieve controlled exposure to five target factors, whilst considering levels of diversification and capacity. All information presented for the FTSE EM Static Multifactor portfolio is back-tested. Back-tested performance is not actual performance, but is hypothetical. Although back-tested data may be prepared with the benefit of hindsight, these calculations are based on the same methodology that was in effect when the index was officially launched. Index returns do not reflect payment of any sales charges or fees. Performance, actual or hypothetical, is not a guarantee future results. An investment cannot be made in an index.

Exhibit A4b: FTSE EM dynamic multifactor strategy performance statistics (January 2005–September 2018).

	Return	Standard deviation	Excess return	Sharpe ratio	Information ratio	Max drawdown	Skewness
FTSE EM Dynamic Multifactor Strategy	13.78%	20.70%	5.82%	0.61	1.11	−53.61%	0.03
FTSE EM Static Multifactor Portfolio	11.42%	19.79%	3.46%	0.52	0.83	−53.74%	−0.52
FTSE EM Index	7.96%	21.76%	–	0.31	0.00	−61.07%	−0.50

Source: FTSE Russell and Bloomberg as of 9/30/18. Average annual returns. Results do not include transaction costs. Sample dictated by data availability. Please see Exhibit A5 for time periods of Maximum Drawdown and Endnotes for definitions.

Exhibit A5: Time periods of maximum drawdown and recovery.

	Begin date	End date
Russell 1000 Low Volatility Factor Index	10/31/2007	2/29/2012
Russell 1000 Momentum Factor Index	8/31/2000	9/30/2007
Russell 1000 Quality Factor Index	3/31/2000	4/30/2007
Russell 1000 Size Factor Index	5/31/2007	12/31/2010
Russell 1000 Value Factor Index	5/31/2007	3/31/2012
Russell 1000 Dynamic Multifactor Strategy	10/31/2007	12/31/2009
Russell 1000 Comprehensive Index	5/31/2007	2/28/2011
Russell 1000 Index	10/31/2007	2/28/2011
Russell 2000 Dynamic Multifactor Strategy	6/30/2017	2/28/2010
Russell 2000 Comprehensive Index	5/31/2017	2/28/2011
Russell 2000 Index	5/31/2017	2/28/2011
FTSE DM ex USA Dynamic Multifactor Strategy	10/31/2007	9/30/2010
FTSE DM ex USA Static Multifactor Portfolio	10/31/2007	1/31/2013
FTSE DM ex USA Index	10/31/2007	2/28/2014
FTSE EM Dynamic Multifactor Strategy	10/31/2007	11/30/2009
FTSE EM Static Multifactor Portfolio	10/31/2007	9/30/2010
FTSE EM Index	10/31/2007	4/29/2011

Exhibit 6b. Results are reported in Exhibit A3 and Exhibit A4 for the FTSE Developed Markets ex-USA and FTSE Emerging Markets benchmarks, respectively. In both cases, the dynamic factor implementation strongly outperformed both the market cap benchmarks and the static multifactor portfolios, with average annual excess returns in the range of 5.8%–6.8% versus benchmark and 2.3%–2.5% versus the static multifactor portfolio. Given an average one-way annual turnover of 150%, and estimated transaction costs of 10–20 bps for Developed Markets—ex USA and 25–50 bps for Emerging Markets, per 100% turnover, these results are economically significant also after transaction costs.

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Notes

1 The size effect was first shown in Banz (1981), and the book-to-market effect first appeared in Statman (1980) and subsequently in Rosenberg, Reid, and Lanstein (1985).

2 The investment effect was identified by Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), and Polk and Sapienza (2009). The profitability effect was introduced by Haugen and Baker (1996) and confirmed first in Vuolteenaho (2002) and later in Novy-Marx (2013).

3 Asness, Friedman, Krail, and Liew (2000) also document similar time-variation in value premia. Recent work by Asness, Liew, Pedersen, and Thapar (2017) and Baba-Yara, Boons, and Tamoni (2018) study these patterns in other asset classes.

4 Additionally, r stands for returns, E stands for expectations and d for dividends.

[5] Thus, this accounting identity also takes no stance on the way in which either aggregate discount rates or expected cash flows may propagate through time.

[6] Each factor index starts with the market cap weighted Russell 1000 Index, then multiplies the market cap weight by a normalized composite score of the relevant metrics for the given factor in order to create the factor index.

[7] Campbell and Vuolteenaho (2004) and others rescale cash-flow sensitivities when measuring cash-flow beta so that cash-flow and discount-rate betas sum to market beta. This purely-cosmetic transformation facilitates comparison across pricing tests of two-beta and single-beta models. We simply report the raw sensitivity which is proportional to their cash-flow beta.

[8] The Russell Comprehensive Factor Index uses a common methodology to achieve controlled exposure to five target factors, whilst considering levels of diversification and capacity.

[9] Information on the OECD composite leading indicators is available at https://www.oecd.org/sdd/leading-indicators/oecdcompositeleadingindicatorsreferenceturningpointsandcomponentseries.htm

[10] We source first vintage economic statistics from the Alfred database of the Federal Reserve.

[11] For example, our global risk appetite indicator has correlations ranging between 0.70-0.75 with indicators such as the Global Manufacturing PMI survey, the Global Employment PMI Manufacturing survey and global industrial production growth. These correlations are all statistically significant at the 99% confidence level. In addition, risk appetite exhibits leading properties in the identification of cyclical turning points in these variables by 2–3 months. See also de Longis and Ellis (2019).

[12] In particular, this adjustment takes place in the expansion regime, where an otherwise desired double tilt to size and value is reduced to a single tilt, given interaction effects with a double tilt on momentum. A simultaneous double tilt to the three factors would lead to excessive concentration in less liquid, smaller capitalization stocks, with detrimental implications for turnover and transaction costs.

[13] PMI Manufacturing surveys are well-known and commonly used leading indicators of GDP growth across countries, given their coverage of cyclical industries and timely release on a monthly basis.

[14] See Appendix II for details.

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