Time-Series Variation in Factor Premia:
The Influence of the Business Cycle

Christopher Polk
London School of Economics

Mo Haghbin
OppenheimerFunds

Alessio de Longis
OppenheimerFunds

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I. Introduction

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 achieve superior 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 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 size have relatively large cash-flow betas while other strategies such as low-volatility and quality have relatively low cash-flow betas. Momentum, consistent with the transitory nature of its signal, exhibits 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, outperforms a static allocation to these factors.

Section II summarizes previous literature and the current smart beta environment. Section III motivates our approach to linking time-variation in factor premia to the business cycle. Section IV discusses data and methodology. Section V presents the empirical results, while Section VI concludes.

II. Factors and Factor Rotation

a. 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

[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).

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 superior risk-adjusted returns for investors by combining two or more of these factors.

Globally, there is a total of $85 billion of assets under management in multifactor ETFs as of Sept 30, 2018. Moreover, this number has continued to increase across all smart beta categories, with year-to-date flows of $12.5 billion. According to Morningstar, there are now over 1,500 single-factor ETFs, representing $422 billion in assets under management. The overall category has seen rapid growth with assets increasing nearly 800% since 2012.

b. 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

[3] In work initiated subsequent to Cohen, Polk, and Vuolteenaho (2003), 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.

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.

III. 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:

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

$N_{CF,t+1}$ 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

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

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 show that small stocks and value stocks have 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.

[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.

IV. 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 plots the cumulative performance and provides some key summary statistics.

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) & 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.	Standard deviation of 5 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.

[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.

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

Exhibit 2: Single Factor Cumulative Performance

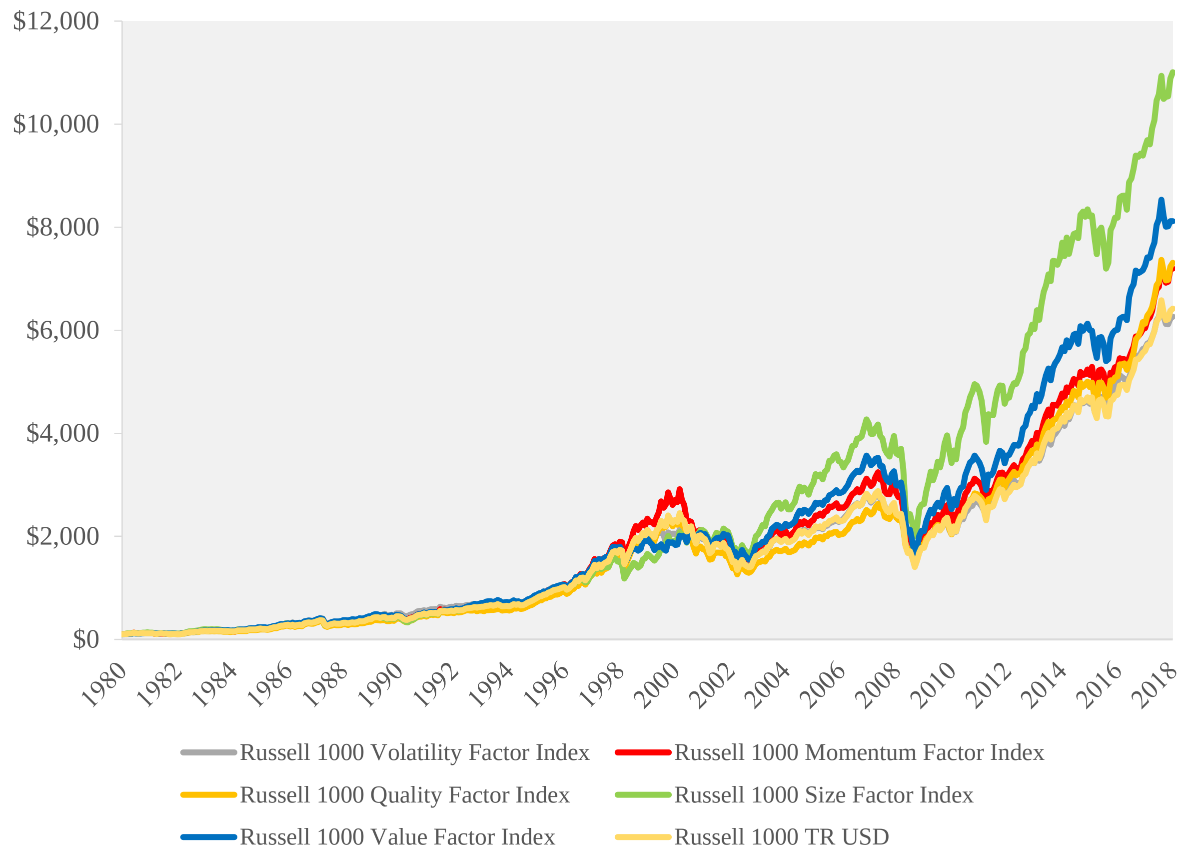


Exhibit 2 Con't: Single Factor Performance Characteristics

	Return	Standard Deviation	Excess Return	Sharpe Ratio	Information Ratio	Max Drawdown	Up Capture Ratio	Down Capture Ratio
Russell 1000 Low Volatility Factor Index	11.67	12.87	-0.03	0.54	-0.01	-46.90	87.37	78.64
Russell 1000 Momentum Factor Index	12.06	15.00	0.36	0.49	0.17	-49.13	100.82	99.24
Russell 1000 Quality Factor Index	12.09	14.91	0.38	0.49	0.13	-47.13	100.12	97.90
Russell 1000 Size Factor Index	13.22	16.57	1.52	0.51	0.26	-53.00	107.71	103.99
Russell 1000 Value Factor Index	12.34	14.71	0.64	0.51	0.15	-54.35	97.89	92.56
Russell 1000 TR USD	11.70	14.81	0.00	0.47	-	-51.13	100.00	100.00

Source: FTSE Russell as of 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. The performance results shown assume that no cash was added to or assets withdrawn from the hypothetical investment and that all dividends, gains and other earnings in the account were reinvested in accordance with index rules. No management fees or brokerage expenses were deducted from the hypothetical performance shown, except where indicated. Indices do not lend securities, and no revenues from securities lending were added to the performance shown. In addition, the results actual investors might have achieved would be different from those shown here, because of differences in the timing, amounts invested, withdrawals if any, and fees and expenses associated with an investment in the index.

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 3: Factor Returns Excess Return Correlation (July 1980-September 2018)

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

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

Exhibit 4 reports the ranked realized annual returns of the factors as well as the benchmark. The historical returns on these factors 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.

Exhibit 4: Calendar Year Factor Returns

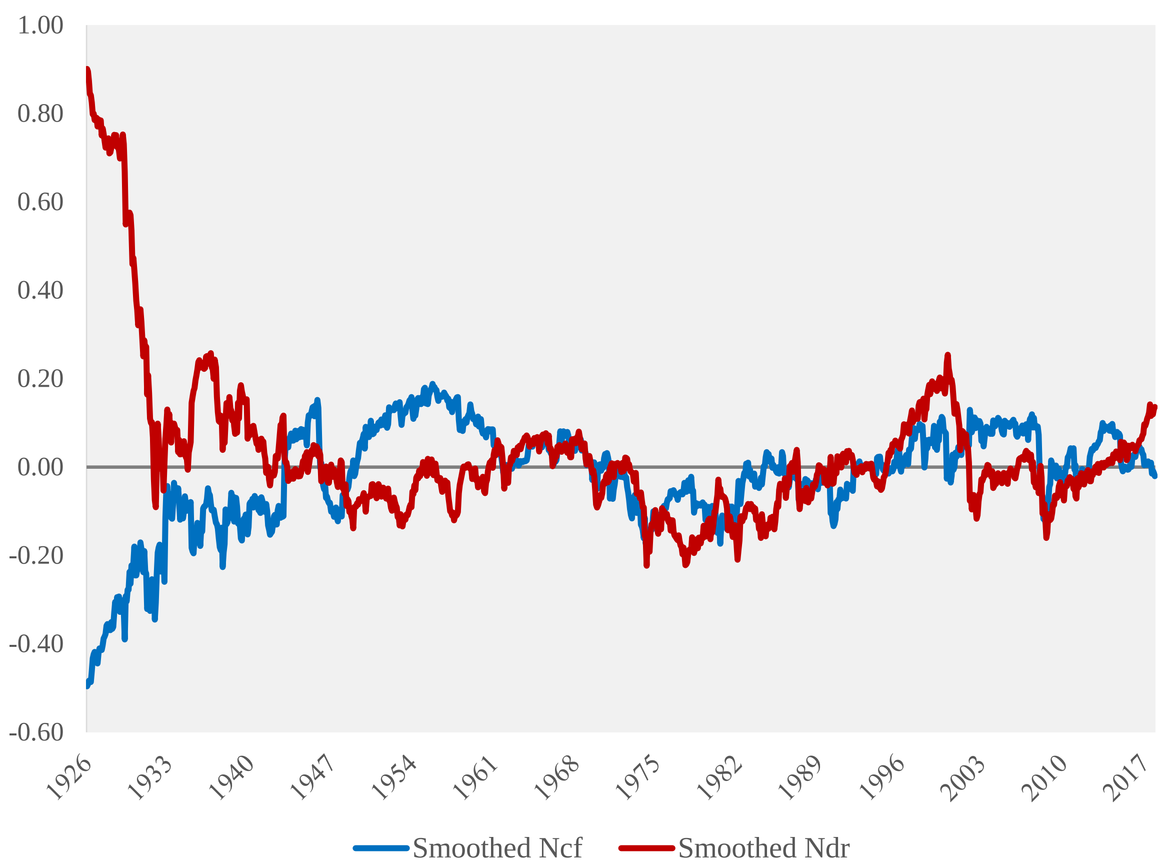
2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018 (YTD)
44.39	18.00	11.08	19.43	11.56	-31.10	41.73	27.76	8.46	19.18	36.60	15.85	3.06	18.66	28.07	13.90
29.99	16.64	9.21	18.29	9.13	-31.14	28.43	20.13	8.46	18.82	36.38	13.33	2.69	15.99	22.83	13.34
29.89	11.77	8.35	15.46	5.77	-36.66	26.72	17.07	2.28	16.42	33.58	13.24	2.11	12.05	21.69	10.49
26.92	11.64	7.54	14.59	3.92	-36.74	24.90	16.10	1.80	16.09	33.11	12.88	0.92	11.56	20.00	9.30
24.21	11.40	6.27	14.30	3.70	-37.57	22.44	14.55	1.50	15.45	31.66	12.65	-2.26	10.71	19.74	8.95
20.59	10.50	4.24	14.26	3.48	-37.60	17.85	11.83	-1.17	13.25	29.61	11.32	-3.34	7.94	18.25	5.24

Momentum	Quality	Size	Value	Volatility	Market

Source: Bloomberg as of 9/30/18. 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. The performance results shown assume that no cash was added to or assets withdrawn from the hypothetical investment and that all dividends, gains and other earnings in the account were reinvested in accordance with index rules. No management fees or brokerage expenses were deducted from the hypothetical performance shown, except where indicated. Indices do not lend securities, and no revenues from securities lending were added to the performance shown. In addition, the results actual investors might have achieved would be different from those shown here, because of differences in the timing, amounts invested, withdrawals if any, and fees and expenses associated with an investment in the index.

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 5 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.

Exhibit 5: Smoothed Components of Aggregate Returns (July 1926 – June 2018)



V. Empirical Results

a. 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

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

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 6 documents that the factors we study have differential exposures to aggregate cash-flow news. In particular, size, and to some degree value have sensitivities that are higher than the Russell 1000 index, and clearly higher than a static multifactor approach. Momentum also exhibits 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 have 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 to economic fundamentals.

[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.

Exhibit 6: 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 Factor Index	0.01	0.91	0.16
	(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.

b. Forecasting Fundamental News

To anticipate the evolution of the economic cycle, we construct a composite business cycle indicator to define four macro regimes: recovery, expansion, slowdown and contraction:

Recovery: growth below trend and accelerating

Expansion: growth above trend and accelerating

Slowdown: growth above trend and decelerating

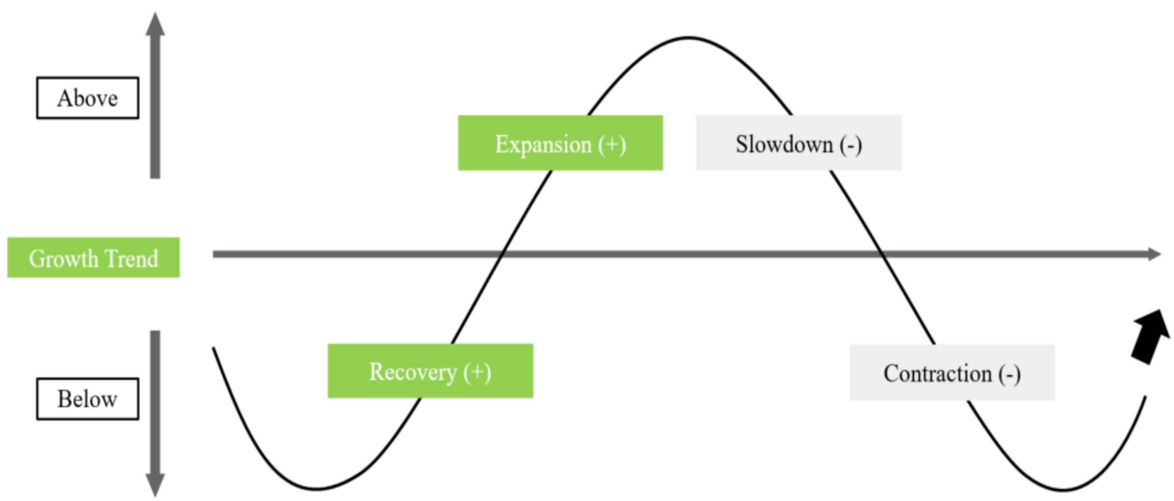
Contraction: growth below trend and decelerating

Exhibit 7 provides a stylized plot of the business cycle regimes we aim to measure. Our composite business cycle framework uses several leading indicators of economic activity, combining information from economic data and global risk appetite extracted from common variations in global risk premia.

First, we 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 construction of the U.S. composite leading indicator. 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[9]. Finally, these normalized variables are aggregated with equal weights into a composite index.

Second, we estimate the expected acceleration or deceleration 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.

Exhibit 7: Business Cycle Regimes



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 are tied to risk aversion and the amount of risk in the economy. Both of these objects have been shown to be negatively correlated with

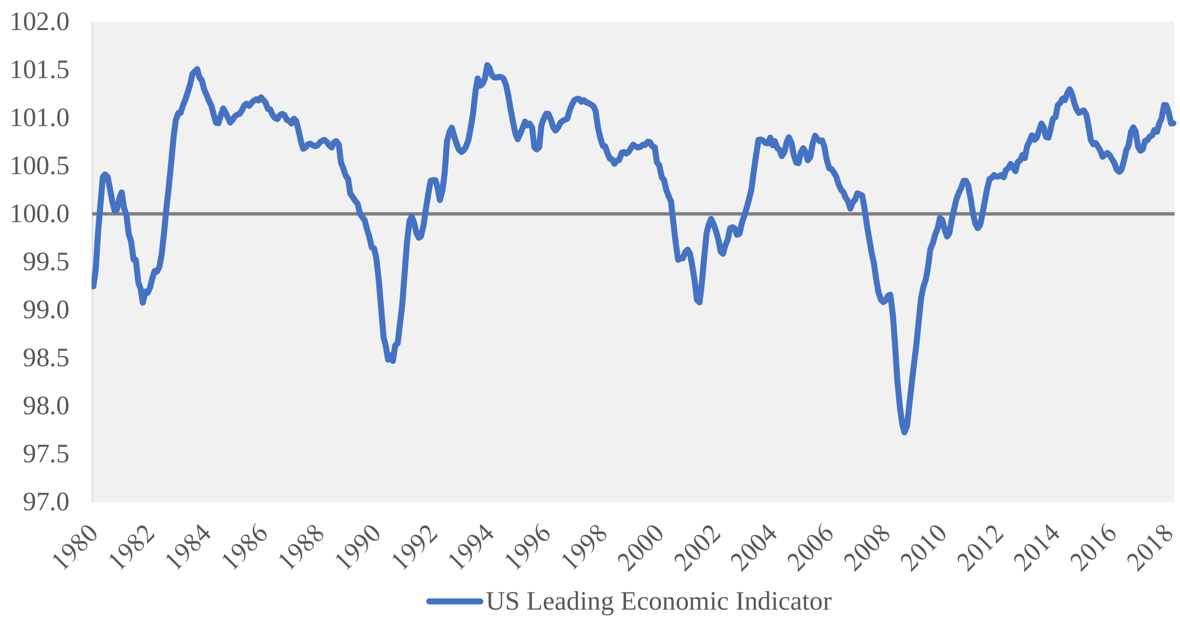
[9] We source first vintage economic statistics from the Alfred database of the Federal Reserve.

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 risk premia. Polk, Thompson, and Vuolteenaho (2006) show how cross-sectional techniques can be used to forecast time-variation in the market risk premium. In a related fashion, de Longis and Ellis (2017) illustrate how risk appetite has a positive and statistically significant correlation with several business cycle indicators, with a lead of several months. Following their methodology, we define global risk appetite as the incremental return received by investors for taking an incremental unit of risk in global financial markets, and it is constructed using country-level equity, government bond and corporate bond indices across both developed and emerging markets. [10]

Exhibit 8 plots these two components of our regime identification methodology.

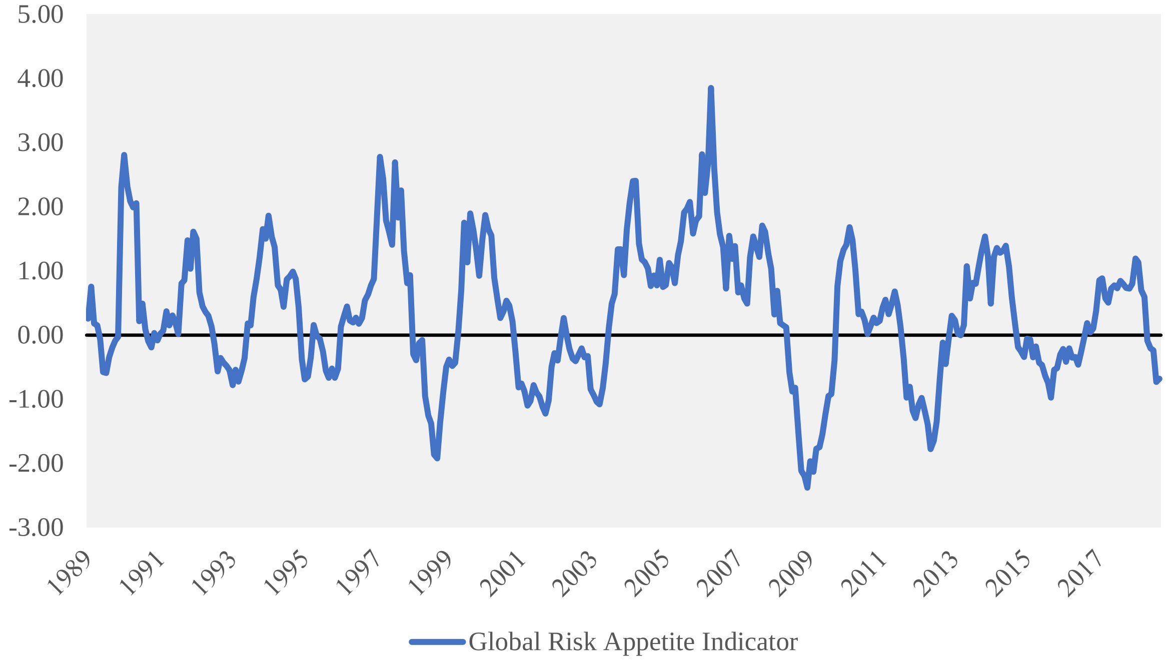
Exhibit 8: U.S. Leading Economic Indicators



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

[10] Earlier related work using similar methodologies includes Kumar and Persaud (2002) and Slok and Kennedy (2004).

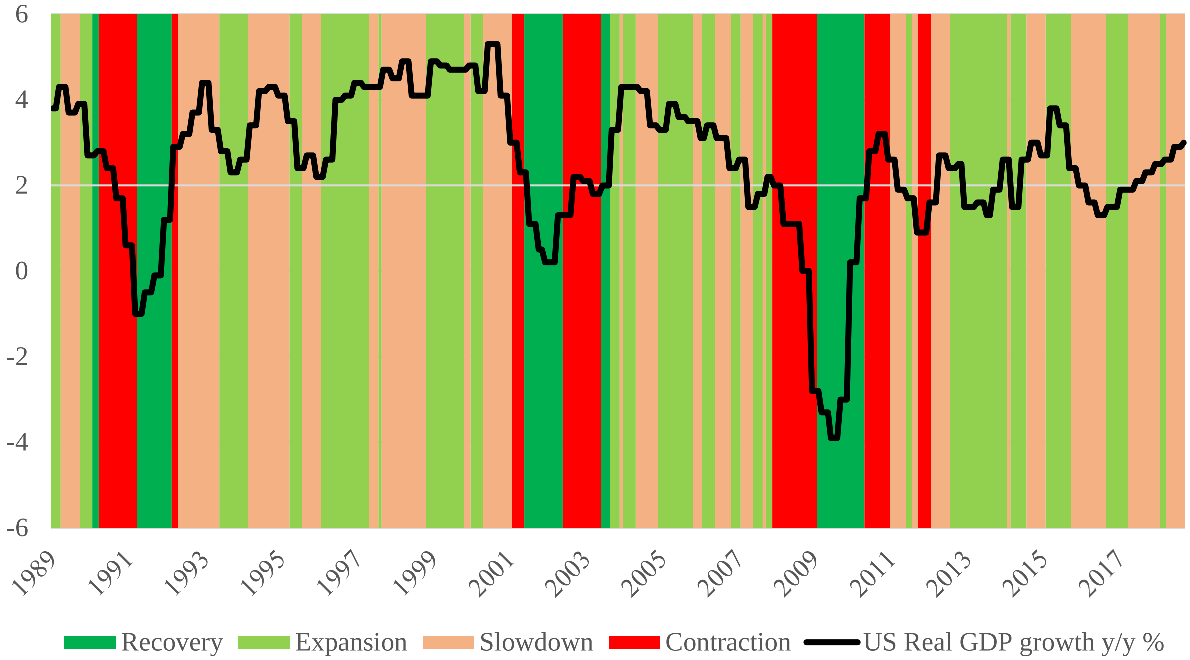
Exhibit 8: Continued: Global Risk Appetite Indicator



Source: Bloomberg, FTSE Russell, MSCI, JPMorgan as of 9/30/2018. Sample time-period dictated by data availability.

Our final composite business cycle framework combines the U.S. leading economic indicator and global risk appetite to define the four stages of the business cycle, illustrated in Exhibit 9. We plot realized GDP growth over our ex-ante regime classification. As Exhibit 9 makes clear, our regime classification has significant predictive content.

Exhibit 9: Business Cycle Regime Identification



Source: Bureau of Economic Analysis as of 9/30/2018. Sample time-period dictated by data availability.

c. 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 6. 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 signal, we only measure contemporaneous sensitivities. Exhibit 10 reports that the momentum factor exhibits clear variation in relative cash-flow sensitivity across the four regimes. Specifically, the Russell 1000 momentum strategy has 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.

Exhibit 10: Momentum Factor's Conditional Cash-Flow Sensitivity (January 1989 – June 2018)

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

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

With these facts in hand, we examine combinations of these five factors based on the regime/tilt matrix described in Exhibit 11. 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[11]. Exhibit 11 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 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: Factor Tilts through the Business Cycle

Factor Overweights 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 Overweights for Other Russell Indices					
Russell 1000	0	0	0	0	0
R1 Comprehensive Factor	1	1	1	1	1

Exhibit 12 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 have 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.

[11] 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 liquidity, smaller capitalization stocks, with negative implications for turnover and transaction costs.

Exhibit 12: Cash-Flow Sensitivity by Regime Portfolio (July 1980 – June 2018)

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

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

Finally, in Exhibit 13, 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 has 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 has 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: Composite Portfolio's Cash-Flow Sensitivity (January 1989 – June 2018)

	Constant	Cash-Flow News Sensitivity	R^2
Unconditional (N=354)	0.00 (1.14)	0.19 (3.83)	0.04
Recovery or Expansion (N=167)	0.00 (2.49)	0.10 (1.14)	0.00
Slowdown or Contraction (N=187)	0.00 (-0.67)	0.23 (3.78)	0.07

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

Exhibit 14 puts this all together, reporting the excess returns and associated information ratios provided by the dynamic multifactor model. The dynamic implementation strongly outperforms both the Russell 1000 Index and the static multifactor implementation of the Russell Comprehensive Factor Index, with average annual excess returns of about 5% and 2.5% over these two benchmarks. Furthermore, given an average one-way annual turnover of 150% and estimated transaction costs of 7-10bps per 100% turnover, these results are economically significant also after transaction costs.

Exhibit 14: 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 Comprehensive Factor Index	1.11% (5.43)	0.17% (2.11)	
Russell 1000 Dynamic Multifactor Strategy	1.31% (6.20)	0.37% (4.26)	0.20% (2.40)

Source: FactSet and Bloomberg as of 9/30/18. Mean monthly returns, non-annualized. We report *t* statistics in parentheses. Results do not include transaction costs. The Russell Comprehensive Factor Index uses a common methodology to achieve controlled exposure to five target factors, whilst considering levels of diversification and capacity.

Exhibit 14 Con't: Dynamic Multifactor Strategy Performance (January 1989 – September 2018)

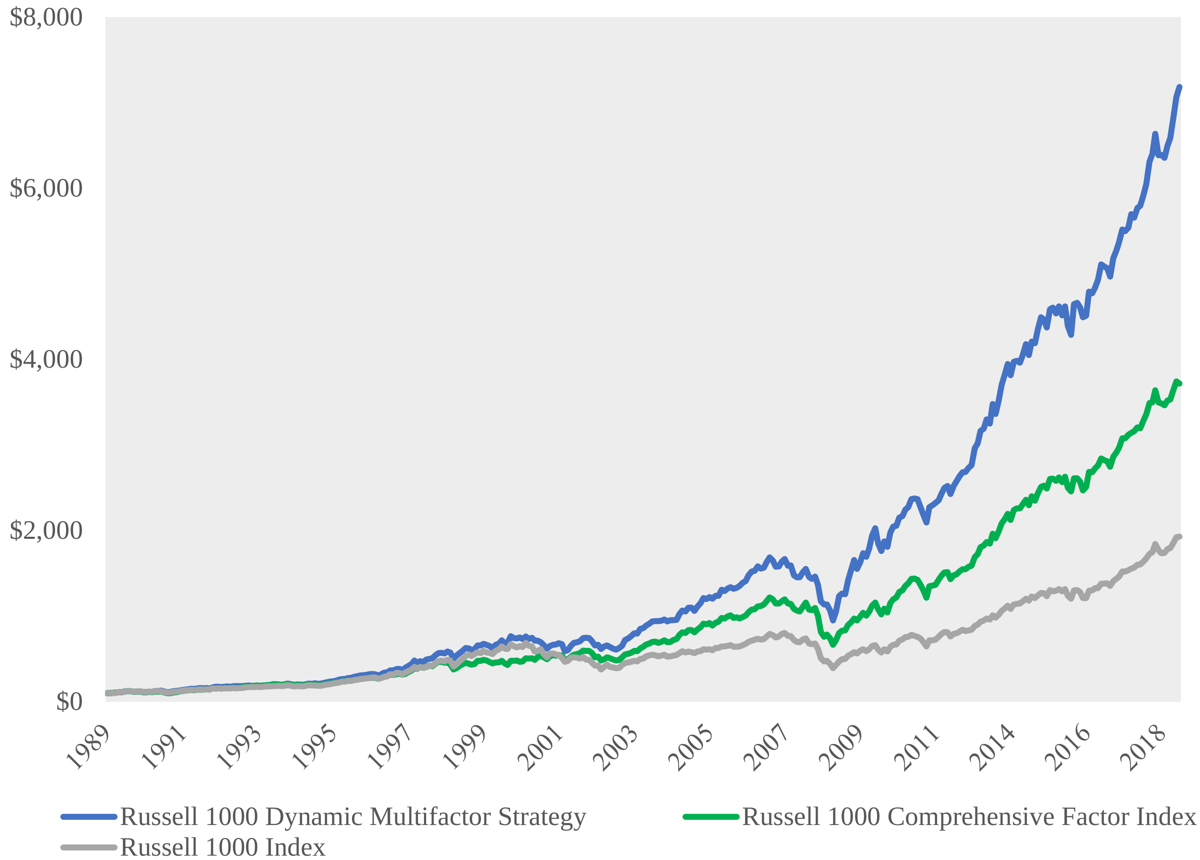


Exhibit 14 Con't: Dynamic Multifactor Strategy Performance Characteristics (January 1989 – September 2018)

	Return	Standard Deviation	Excess Return	Sharpe Ratio	Information Ratio	Max Drawdown	Up Capture Ratio	Down Capture Ratio
Russell 1000 Dynamic Multifactor Strategy	15.76	13.78	5.05	0.92	0.89	-44.83	102.65	74.06
Russell 1000 Comprehensive Factor Index	13.12	13.33	2.41	0.77	0.46	-45.53	96.36	79.39
Russell 1000 Index	10.71	14.20	0.00	0.58	-	-51.13	100.00	100.00

Source: FactSet and Bloomberg as of 9/30/18. Average annual returns. We report *t* statistics in parentheses. Results do not include transaction costs. **Russell OFI 1000 index** inception date: November 8, 2017. The returns of the Index prior to 11/8/17 represent hypothetical pre-inception index performance (PIP) to illustrate how the Indices may have performed had they been in existence for the time period prior to 11/8/17. The performance results shown assume that no cash was added to or assets withdrawn from the hypothetical investment and that all dividends, gains and other earnings in the account were reinvested in accordance with index rules. No management fees or brokerage expenses were deducted from the hypothetical performance shown, except where indicated. Indices do not lend securities, and no revenues from securities lending were added to the performance shown. In addition, the results actual investors might have achieved would be different from those shown here, because of differences in the timing, amounts invested, withdrawals if any, and fees and expenses associated with an investment in the index

VI. 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 generate Information Ratios nearly twice as large as static implementations, while generating excess returns of about 5% per annum versus their benchmark index over the past 30 years. Results are statistically and economically significant after accounting for transaction costs, capacity and turnover. Finally, these conclusions seem robust across multiple applications. In particular, we obtain similar results in other market segments such as the Russell 2000 universe, as well as other regions such as European equities, international equities and emerging markets, which we plan to document in future work.

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Appendix

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). 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 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).

Appendix Exhibit 1 presents CGPT's estimation of the monthly VAR. Standard errors include a Newey-West adjustment based on 12 lags.

	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

In particular, CGPT estimate a heteroskedastic VAR,

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

where x_{t+1} is the nx1 vector of state variables with rM as the first element, σ_{t+1}^2 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×1 vector $e_1$with zero elements except for a unit first element. Their structure implies

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

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

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

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