Business Cycle–Related Timing of Alternative Risk Premia Strategies

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KEY FINDINGS

- The authors show that the returns of certain alternative risk premia strategies are statistically significant related to economic conditions.
- Evidence provided give no indication that the documented performance patterns are driven by underlying beta exposure.
- Given the observed macroeconomic sensitivities the authors construct a risk premia timing strategy that add marginal performance with low turnover to a risk-parity portfolio.

ABSTRACT: *Time variation in risk premia is not a violation of market efficiency but rather a reflection of time-varying economic rewards. By analyzing macroeconomic sensitivities (proxying for good and bad times), the authors show that time-varying returns of certain alternative risk premia strategies are significantly related to economic conditions. On the basis of identified return patterns, the authors construct a risk premia timing strategy that adds statistically significant marginal performance with low turnover. They confront data-mining concerns by successfully cross-validating their model across various investment universes.*

TOPICS: ***Analysis of individual factors/risk premia, real assets/alternative investments/private equity****

Theoretical asset pricing models conjecture that returns on risky assets depend on economic states of the world that resemble business cycle–related risks. Inflation, real rates, and term spreads are known as state variables that help predict time-varying risk premia. Time variation in risk premia is not a violation of market efficiency but rather a reflection of the fact that economic rewards for taking on risk must be large when economic times are bad. There is ample empirical evidence that the financial payoffs of asset classes such as stocks and bonds vary with the business cycle. Much work has been put into determining cross-sectional variation in expected returns of traditional assets using macroeconomic variables (e.g., Gertler and Gilchrist 1994; Kiyotaki and Moore 1997; Berk, Green, and Naik 1999; Perez-Quiros and Timmermann 2000).

More recently, the attention of researchers has also turned to explaining time-varying returns of equity style factors by approximating the state and development of the business cycle (Ferson and Harvey 1991). Chordia and Shivakumar (2002) analyze dynamic return patterns of momentum strategies. Using a set of lagged standard

*All articles are now categorized by topics and subtopics. **View at PM-Research.com.**

macroeconomic variables to forecast 1-month-ahead stock returns, the authors show that the predicted part of returns is the primary cause of the observed momentum premium. Hodges et al. (2017) search for sources of cross-sectional and time-series information to predict the premiums of equity factor strategies using smart beta indexes and conclude that timing equity factors on the basis of macroeconomic conditions can generate excess returns to a passive allocation approach.

Macroeconomic indicators as explanatory variables for observable cross-sectional return differences are well established. In this article, we examine the transferability of alternative risk premia (ARP). Few studies emerged relating the behavior of documented ARP to the macroeconomic environment. Christiansen, Ranaldo, and Söderlind (2011) investigate the time-varying systematic risk of FX carry trade strategies across different market regimes. To distinguish between high- and low-risk environments, proxies commonly used to measure market and liquidity risk are adopted. The authors show that in turbulent times, carry trade strategies record a coincident increase in volatility and exposure to other risky assets. Ang et al. (2018) analyze the volatility risk premium in the stock market, which refers to the phenomenon that option-implied volatility tends to exceed the realized volatility of the same underlying asset over time. Given the nature of a volatility-selling strategy, major drawdowns are recorded when the underlying asset experiences sudden large losses as investors revise their expectations. Studying the bond market, Asvanunt and Richardson (2016) confirm the existence of a positive premium for bearing exposure to default risk. The authors construct a time series of corporate bond returns in excess of Treasury bond returns (adjusted for any duration differences). The measured excess return of corporate bonds, referred to as "credit risk premium," is more pronounced in regimes of economic growth and negative in periods of increasing inflation and economic slowdown.

It is common practice to use different risk parity models individually or in combination to strategically optimize the allocation of ARP strategies. In this article, we explicitly analyze the macroeconomic sensitivities and present an approach for actively allocating ARP strategies conditional on the prevailing economic regime. The presented findings give an implication for the performance potential in a tactical framework.

Our work builds on Ilmanen, Maloney, and Ross (2014), who examine macroeconomic sensitivities of various asset classes. Considering different macroeconomic variables and inflation/growth scenarios, the authors report return patterns for traditional asset classes fairly in line with economic intuition. In addition, the authors include five simulated long/short style premia composites in their analysis. However, given the presented macroeconomic sensitivities for momentum, value, carry, defensive, and trend-following strategies, the authors find little evidence to suggest that style premia performance relates to the economic environment as results for conditional returns are insignificant.

We enhance the approach from Ilmanen, Maloney, and Ross (2014) in numerous ways. Whereas the authors use aggregated-style premia strategies combining different asset classes, we investigate asset class–specific risk premia strategies to increase the probability of identifying meaningful return patterns. Besides sharing similar rationale, strategy returns are assumed to be related specifically to the underlying assets. Furthermore, instead of considering a set of common economic variables, we construct a slightly more complex but intuitive business cycle model to approximate and predict the state of the economic environment. Whereas many articles use statistical properties of the assets themselves for regime definitions, we adopt a fundamental approach that uses economic data for explicitly identifying the prevailing regime in contrast to estimating probabilities. The model enables us to analyze conditional returns and to deduce transparent regime-based allocation scenarios.

We extend the existing literature for ARP by analyzing macroeconomic sensitivities for a diversified basket of tradable ARP strategies. The key issue addressed in this article is whether such dependencies can be observed and exploited in a portfolio construction context. The approach closest to ours is from Blin et al. (2018). To identify business cycles these authors use a (parsimoniously described) proprietary nowcasting procedure that makes extensive use of large data sets. Also, they find positive timing abilities in the same order of magnitude and significance as our less demanding procedure. In contrast to our article, no cross-validation across related universes takes place.

The rest of this article is organized as follows: In the next section, the methodology of the business cycle model is described in detail. The third section discusses the sample and data. The fourth presents findings concerning the macroeconomic sensitivities of ARP strategies and then analyzes the return potential of an active portfolio allocation approach. To validate conclusions made based on our economic model, we investigate conditional returns of different investment classes and compare these with previous findings and economic intuition in the fifth section. In the final section, we put our results into perspective and give suggestions for future studies.

METHODOLOGY

The purpose of a business cycle model is to capture the global economic environment by combining various macroeconomic data. Given the amount of literature and research on economic models existing, we opt for adopting and adjusting a model suited for our requirements. Our approach is an enhancement of the economic model developed by Van Vliet and Blitz (2011) as the methodology is intuitive, robust, and easily applicable. The model makes use of economic data to construct an indicator for explicitly identifying the prevailing economic regime. In particular, the aggregated regime indicator should grasp the future development of the business cycle and infer the characteristic regime according to the economic cycle classification by the National Bureau of Economic Research. It enables us to analyze conditional asset returns and to deduce transparent regime-based allocation scenarios.

Besides the necessary predictive power of the aggregated indicator, the potential of the business cycle model relies on its sensitivity to allow for early signal generation without generating too many false positives. Highly reactive trading indicators typically result in inefficient asset allocation and excessive turnover. To achieve the desired trade-off, we combine lagging indicators with more volatile but leading indicators. Details on the selected variables are provided in the next section.

We use an aggregated indicator to derive the characteristic regime. Each phase of the ideal-type economic cycle is defined by two criteria—the current level of the indicator and its change from the last observation. To ensure comparability and combinability of the regarded macroeconomic data, the variables have been standardized. The Z-scores are calculated at the end of each month under the expanding window approach to avoid look-ahead bias.[1] We make use of the entire historical data given at the point in time to benefit from the inherent "learning effect."[2] To limit the influence of individual variables we cap the Z-score to three standard deviations on either side. An equal-weighted Z-score of the selected macroeconomic variables equates to the level of the overall regime indicator. Although the state of the economic environment is represented by the sign of the aggregated Z-score, its trend shall be captured by the change of the level over the defined reference period.

To account for swift changes in Z-scores calculated on a few observations, we use at least a 3-year training period before we start generating trading signals based on the regime indicator. The four business cycle regimes are defined as follows:

- expansion: Z-score positive and increasing
- peak: Z-score positive but decreasing
- recession: Z-score negative and decreasing
- recovery: Z-score negative but increasing

To limit the number of regime switches (and thereby the turnover), two consecutive periods of uniform changes or a monthly change of more than 1 standard deviation above its average is required to signalize a sustainable change in the business cycle regime.

We are fully aware that there might be more dynamic or sophisticated approaches for predicting the economic business cycle, but the primary purpose of this study is to analyze and exploit possible macroeconomic sensitivities of ARP, so the model considered meets the requirements.

DATA

Business Cycle

We use monthly data from March 1998 as they represent the longest available common data history of the used macroeconomic variables.

Besides complying with the specific requirements related to the methodology mentioned above, the variables should capture information from different

[1] Median is used instead of mean for standardization to reduce the impact of outliers.

[2] For data samples with a much longer look-back it might be necessary to operate with a rolling window approach to account for structural changes in the long run.

macroeconomic dimensions influencing the development of the business cycle. Therefore, we consider five indicators represented by the following macroeconomic data:

- *Unemployment* is defined by the seasonally adjusted US unemployment rate (USURTOT Index).
- The Organisation for Economic Co-operation and Development (OECD) composite leading indicator (CLI) is an approximation of economic activity itself to reflect adjustments to expectations concerning *economic growth*. As the officially announced GDP growth is a lagging indicator, substitute variables with a higher frequency are selected to provide a monthly estimate of an otherwise quarterly released data set.[3]
- *Producer sentiment* is expressed by combining Markit Global Manufacturing PMI (MPMIGLMA Index) and ISM Non-Manufacturing NMI (NAPMNMI Index). Both survey-based indexes try to forecast business activity and climate by polling purchasing and supply managers in the manufacturing as well as in the service sector.
- The Conference Board Consumer Confidence Index (CONCCONF Index)[4] and the University of Michigan Consumer Sentiment Index (CONSSENT Index)[5] are selected to measure *consumer sentiment* as the degree of optimism that consumers are expressing through their economic expectations and financial activities.
- *Financial market stress* can be thought of as an interruption to its normal functioning often related to either increased uncertainty about the fundamental value of assets or about the behavior of other investors. We adopt the approach of the Kansas City Financial Stress Index (KCFSINDX Index) to construct a financial stress indicator independent of the release date. The combined indicator includes different spread, volatility, and correlation data to reflect possible market frictions. With the actual KCFS Index being released only once at the beginning of each month and our business cycle indicator being calculated at its end, we significantly reduce the information lag provided by an otherwise delayed data processing.[6]

Each of the *five dimensions* contributes equally to the overall regime indicator. All macroeconomic data are retrieved from Bloomberg and the FRED database of the Federal Reserve Bank of St. Louis.[7] Unemployment, financial stress, and all sentiment data are based on their initial releases to reflect the information that would have been available at the time of the forecast.[8] To account for aligned interpretation, the inverse of the unemployment rate and the financial stress indicator with the opposite sign are used for further analysis.

We are aware of the fact that besides looking at global asset returns, we have a minor focus on US macroeconomic data as a result of data limitations. Practically, the effect may be negligible because of the impact the US economy has on the development of global capital markets.

Alternative Risk Premia

For our analysis, we use a well-diversified basket of 25 third-party risk premia strategies developed by a leading investment bank. The data set covers tradable ARP strategies for multiple asset classes, including equities, bonds, currencies, commodities, and rates. Price data for the strategies are provided by Bloomberg.

As the strategies are at least partially back-tested, we apply a haircut on the Sharpe ratio of the simulated sample data based on the approach of Harvey and Liu (2015). The rationale for this is the following. The more optimistic we are on unconditional Sharpe ratios (which are the results of back-tests and hence almost

[3] Data used are end-of-sample figures and could differ from the preliminary figures published earlier. However, direction and magnitude of the monthly change should rarely be affected. Because of standardization, small adjustments to the absolute value are of less importance. Hence, the impact on the business cycle indicator should be rather negligible. For detailed analysis of the effect of revisions, see Nilsson and Guidetti (2008).

Additional information on the methodology of the leading indicator CLI is released on the OECD home page (http://www.oecd.org/sdd/leading-indicators/41629509.pdf).

[4] https://www.conference-board.org.

[5] https://data.sca.isr.umich.edu/.

[6] It is beyond the scope of this article to explain the complete data-generating process. For further details on the selected financial variables and on how they are combined, see, for example, Hakkio and Keeton (2009).

[7] https://fred.stlouisfed.org/.

[8] Data for the ISM Non-Manufacturing NMI are final figures until 2008. From then on, initial release data are available and are used.

surely overestimate future returns), the more pessimistic we will be on timing. Deviating from a diversified portfolio of ARP creates a diversification loss that successful timing needs to overcome. This loss is larger than are the higher Sharpe ratios on individual ARP. Using unadjusted back-test performance will make investors expect unrealistically high payoffs from a static strategy and at the same time impose an unrealistically high burden for the viability of timing strategies. To ensure comparability and account for differences in the risk profile of the underlying strategies, each ARP strategy is scaled to a volatility of 8% per annum (p.a.).

Further details on the considered ARP strategies concerning their functionality are given in Exhibit 1. We note that the ability to directly trade these vehicles makes them an option for individual investors to use in portfolio construction.

Global Multi-Asset Classes

The global portfolio is a representative mix of broad and diversified asset classes, including global equity, rates, credit, and commodity. For practitioners, the model provides a straightforward approach of implementing an approximation of the global portfolio. All indexes are easily investable using exchange-traded funds.

The indexes representing global equity are the MSCI North America, MSCI Europe, MSCI Japan, MSCI Pacific ex Japan, and MSCI Emerging Markets total return indexes. The remaining asset classes are replicated using the BB Barclays Global Government, BB Barclays Global Credit, BB Barclays Global Securitized, BB Barclays Global High Yield, and BB Barclays World Govt Inflation Linked Bonds total return indexes and the gold spot price.

We calculate the daily excess return for EUR-denominated asset classes using DB EONIA TR index as a cash equivalent. To reduce the influence of currency movements on otherwise noisy bond returns we use currency hedged bond benchmarks. All daily data are retrieved by Bloomberg from January 2001 to August 2018.

Equity-Style Factors

Finally, we look at equity-style factors to cross-validate our business cycle model. Although it is well known that variation in stock market risk exposures (dumb beta) can be associated with successful timing, we extend that line of thought and test whether time-varying returns of equity risk factors (smart beta) relate to changes in the prevailing economic regime. For this purpose, we address style factors identified by Fama and French (1993, 2015) and the corresponding global MSCI smart beta indexes. Our universe of choice is given by the Fama–French five-factor model as an alternative investment environment that augments the original three-factor model of market (MKT), size (SMB), and value (HML) with profitability (RMW) and investment factors (CMA). We obtain daily return data for the modeled risk factors from January 2001 to August 2018 published on the website of Kenneth French.[9]

Further, we investigate the economic dependencies of equity style factors momentum, size, value, quality, and minimum volatility provided by the MSCI style indexes.[10] We calculate the daily active returns of MSCI World smart beta indexes using Bloomberg data for the same look-back period. The given data sets are transparent and investable for individuals via exchange-traded funds.

The style factors used enhance our other data set for analyzing conditional returns of risk premia by common equity style factors from different sources.

EMPIRICAL RESULTS

In this section, we report our main findings analyzing conditional return patterns of alternative risk factors and exploiting these for a timing strategy based on the economic regime. To examine the return dependency on the macroeconomic environment, reported conditional performance data are the result of an in-sample analysis. A possible relationship should not be overshadowed by the degree of predictive power the business cycle indicator possesses. Therefore, the monthly returns of the ARP strategies are assigned to the business cycle regime indicated at the end of the same month. In addition, we assess the statistical significance of the observed differences in regime-related

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[10] According to the style factors mentioned, we use the MSCI World Momentum, MSCI World Size, MSCI World Enhanced Value, MSCI World Sector Neutral Quality, and MSCI World Minimum Volatility as related smart beta indexes.

EXHIBIT 1

Detailed Information on Considered Risk Premia Strategies

Risk Premia Strategy	Rationale
Equity Multifactor	Multifactor strategy aims to provide exposure to a number of well-known equity risk premia, such as Momentum and Value.
Equity Defensive	Defensive strategies are designed to provide defensive characteristics during stress scenarios.
Equity Trend FX Trend Interest Rate Trend Commodity Trend Cross Asset Trend	Trend strategies aim to exploit time series trends in asset prices.
Equity Carry Credit Carry FX Carry Interest Rate Carry	Carry strategies overweight high-yielding assets and underweight or short low-yielding assets.
FX Value Interest Rate Value	Value strategies seek premia from overweighting undervalued assets and underweighting or shorting overvalued assets.
Credit Curve Interest Rate Curve Commodity Curve	Curve strategies seek to earn a premium by going long and short different maturities on a yield/futures curve.
Equity Vol. Carry Credit Vol. Carry FX Vol. Carry Interest Rate Vol. Carry Commodity Vol. Carry	Volatility carry strategies aim to harvest a volatility risk premium that arises from supply-and-demand imbalances for options.
Equity Imbalance (1) Equity Imbalance (2) Commodity Imbalance (1) Commodity Imbalance (2)	Imbalance strategies seek to profit from structural imbalances in markets.

performance. The robustness of our findings is critical for the possible applicability of the results to portfolio construction.

Finally, we analyze the performance of a long/short portfolio, which is based on the identified conditional return patterns to give an indication for the potential of regime-related risk premia timing.

Macroeconomic Sensitivities

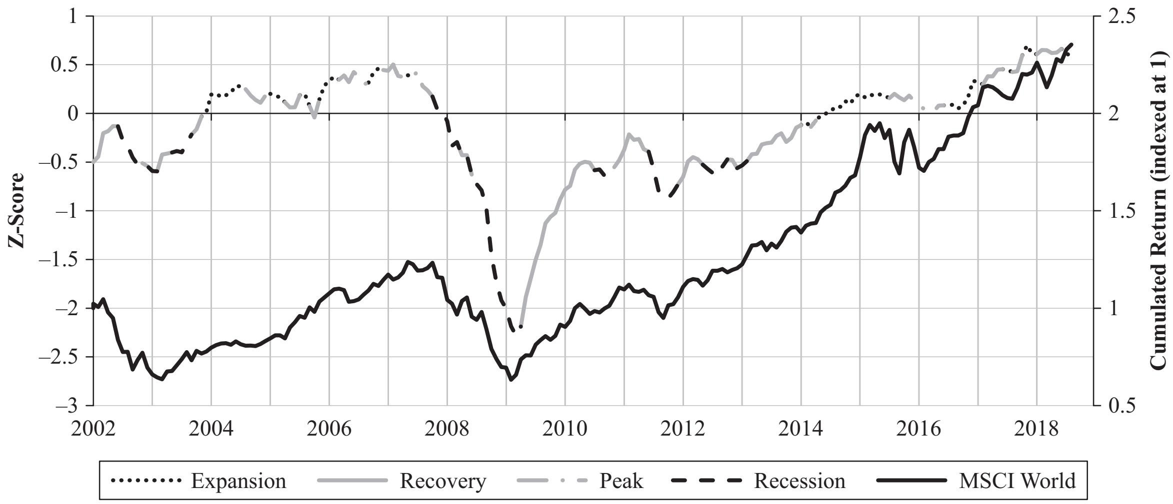
Exhibit 2 displays the business cycle indicator we estimate from January 2002 to August 2018 given the end-of-sample Z-score. The line-type of the chart corresponds to one of the four economic regimes provided by the business cycle model. The regimes accord with economic intuition, and the development of the indicator is correlated, as expected, with the global equity market.

In Exhibit 3, we report the annualized Sharpe ratio of the ARP strategies conditional on each regime of the business cycle. Although the conditional Sharpe ratios of some strategies barely diverge from their overall, unconditional Sharpe ratios; others look to have characteristic return patterns in line with economic expectations concerning cycle-related asset behavior.

For example, the observed return patterns for the Interest Rate Curve strategy might be explained by the dependency of the strategies' performance on the shape of the expected yield curve, which is closely related to the regime of the economic cycle. With the strategy investing in the short end of the curve and selling the long end while maintaining duration neutrality, performance is negative in expansion and peak phases, in which inflation tends to increase, and investors expect the yield curve to steepen. However, conditional strategy

Exhibit 2

Development of the Business Cycle Indicator 2002 to 2018



Notes: The end-of-sample Z-score of the aggregated business cycle indicator is reported on the primary x*-axis. The line-type corresponds to the regime indicated at the point in time. The cumulated monthly performance of the MSCI World AC as a proxy of the global equity market is displayed on the secondary* y*-axis. Performance is indexed at one starting in January 2002. Monthly data are reported from the end of August 2018.*

performance is especially positive in the recession phase as market expectations might turn to future interest rate cuts as monetary policy focuses on stimulating economic growth (Evans and Marshall 2007).

Equally eye-catching is the regime-related performance of various volatility carry strategies. Remarkable, high statistical significance is achieved by the volatility carry strategies of equity and FX. In line with economic intuition, both strategies outperform in the recovery phase as implied volatility tends to trade at a high premium to subsequent realized volatility (Ang et al. 2018). With the uncertainty of market participants and volatility of risky assets typically increasing in the peak phase, this premium likely disappears when implied volatility at which options are sold underestimates future realized volatility. Both carry strategies underperform in this regime.

However, return patterns for trend strategies show no sign of relationship to the economic cycle. Trend strategies typically underperform in nondirectional markets. As the transition phase between regime shifts is often accompanied by changes in cross-asset market trends, the period of below-average strategy performance will last until new trends are established. Hence, inconclusive return patterns might be the result of regime shifts affecting strategies' performance. We explicitly address that issue in the example of the equity momentum factor in later sections.

We use an analysis of variance (ANOVA) to test whether the observed differences in the conditional monthly returns are robust.[11] Overall, almost 50% of the considered ARP strategies have a statistical significance at the 10% level or lower (see Exhibit 3). These results are rather impressive because several strategies are designed to deliver a continuous and unconditional performance contribution. Furthermore, the business cycle indicator is not a perfect match for an underlying economic trend, and the economic condition is not the only expected return dependency.

To confront concerns about the beta neutrality of the risk premia strategies we calculate the conditional betas against global equity and bonds returns. Results of the multivariate regression are reported in Exhibit 4. Although some strategies record high betas in certain regimes, only two of them experience significant, uniform beta exposure in each regime, with one of them being Equity Volatility Carry. It is of little surprise that this strategy has significant equity exposure over all regimes considering the nature of its composition.

[11] We correct for unequal variances across economic regimes by calculating a nonparametric (bootstrapped) test statistic.

EXHIBIT 3
Conditional Sharpe Ratio of Alternative Risk Premia Strategies

	Annualized Sharpe Ratio					ANOVA		
Risk Premia Strategy	**Expansion**	**Peak**	**Recession**	**Recovery**	**Overall**	**Obs.**	***F*-Statistics**	***p* Value**
Equity Multifactor	1.04	0.01	0.23	1.68	0.76	166	1.762	0.157
Equity Vol. Carry	1.87	0.54	1.13	3.02	1.68	198	4.433	0.005***
Equity Trend	0.71	0.32	0.84	0.01	0.44	202	0.648	0.585
Equity Imbalance (1)	0.80	0.05	1.28	1.06	0.86	174	3.747	0.012**
Equity Imbalance (2)	1.53	–0.08	1.35	2.60	0.96	151	2.403	0.070*
Equity Defensive	1.63	0.18	1.03	3.31	1.37	166	2.449	0.066*
Equity Carry	0.93	0.72	–0.12	2.06	0.82	121	1.748	0.161
Credit Carry	0.48	0.25	–0.15	1.78	0.71	123	2.426	0.069*
Credit Curve	0.22	0.30	0.01	1.77	0.59	132	2.327	0.078*
Credit Vol. Carry	0.69	0.82	1.74	1.99	1.52	126	3.217	0.025**
FX Trend	0.89	0.22	0.09	0.80	0.56	202	0.472	0.699
FX Value	0.30	0.06	0.12	0.84	0.28	202	0.344	0.811
FX Vol. Carry	0.13	–0.05	0.29	2.47	0.65	202	4.127	0.007***
FX Carry	0.88	1.29	0.80	0.89	1.00	202	0.402	0.751
Interest Rate Trend	0.47	0.57	1.45	1.16	0.92	202	1.386	0.248
Interest Rate Carry	0.62	1.77	0.89	0.88	0.96	202	0.670	0.570
Interest Rate Vol. Carry	1.22	1.16	–0.47	1.71	0.60	202	3.612	0.014**
Interest Rate Curve	–0.65	–1.01	1.29	0.42	0.26	202	5.228	0.002***
Interest Rate Value	0.53	0.25	1.47	0.78	0.73	202	1.533	0.208
Commodity Vol. Carry	0.44	0.74	1.07	2.33	1.21	186	3.677	0.013**
Commodity Curve	1.67	2.97	0.96	0.72	1.40	202	2.276	0.079*
Commodity Imbalance (1)	0.00	0.65	1.25	1.19	0.81	202	1.802	0.146
Commodity Imbalance (2)	0.84	1.27	0.44	0.62	0.75	202	0.190	0.904
Commodity Trend	0.95	0.51	0.45	–0.26	0.41	202	1.212	0.303
Cross Asset Trend	1.08	0.69	0.61	1.71	1.01	202	0.388	0.759

*Notes: Vol. = volatility; obs. = number of monthly observations given for the data sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.*

However decisive, for the successful implementation of a regime-related timing strategy, it is not the coincident development of subsequent risk factor returns and the economic environment, but it is the capability of predicting future factor returns by forecasting the business cycle.

Portfolio Construction

To assess the possibility of exploiting the observed regime-related return dependencies in portfolio allocation, we set up an active timing strategy. Ahead of portfolio simulation, we need to define active allocation scenarios for each of the business cycle regimes based on our previous findings for macroeconomic sensitivities (see Exhibit 3). To ensure suitability, only ARP strategies with a statistical significance at the 10% level or better are considered for portfolio construction. In addition to the restrictions for robustness, we exclude risk premia strategies with excessive rebalancing costs.[12] The remaining strategies are ordered by the conditional Sharpe ratio in each regime. We select the four strategies with the highest Sharpe ratio and the four with the lowest to form the regime-specific long/short allocation scenarios.

The regime indicator is applied to the timing strategy as follows. Referring to the methodology

[12] The chosen limit results from a trade-off between performance contribution and transaction costs. We consider swap-based rebalancing costs above 50 basis points as excessive.

EXHIBIT 4
Conditional Beta Exposure of Alternative Risk Premia Strategies

	Global Equity					Global Bonds				
Risk Premia Strategy	**Expansion**	**Peak**	**Recession**	**Recovery**	**Overall**	**Expansion**	**Peak**	**Recession**	**Recovery**	**Overall**
Equity Multi Factor	–0.142	–0.016	0.155*	–0.040	0.083	0.187	–0.173	0.097	–0.218	–0.053
Equity Vol. Carry	0.412***	0.484***	0.214**	0.340***	0.290***	–0.502**	–0.302	0.163	0.026	–0.049
Equity Trend	0.728***	0.397**	–0.205***	0.170*	0.015	–0.315*	–0.305	–0.081	–0.100	–0.085
Equity Imbalance (1)	–0.162	0.052	–0.179	–0.188**	–0.163**	0.001	0.125	0.426	0.473**	0.324*
Equity Imbalance (2)	0.241**	0.238	–0.124	–0.017	0.005	–0.581***	–0.102	0.420	0.144	0.024
Equity Defensive	0.244**	0.206	–0.610**	0.062	–0.255**	–0.495**	–0.143	0.399	0.105	0.022
Equity Carry	0.209	0.177**	0.384*	0.354***	0.337***	–0.235	0.003	–0.286	0.109	–0.092
Credit Carry	0.244*	–0.097	0.292*	0.188	0.196**	–0.437*	–0.106	–0.870	0.047	–0.352*
Credit Curve	–0.005	–0.047	0.365***	0.361***	0.281***	–0.168	–0.087	–0.436	0.045	–0.164
Credit Vol. Carry	0.205*	–0.056	0.155	0.088	0.078	–0.423**	–0.349	–0.166	0.469	0.073
FX Trend	0.007	0.158	–0.085	0.024	0.001	0.225	0.029	0.632**	0.242	0.324**
FX Value	–0.004	–0.061	0.166*	0.031	0.081*	–0.159	0.252	–0.670**	–0.124	–0.278**
FX Vol. Carry	0.317*	0.212*	0.052	0.167*	0.130**	–0.176	–0.040	0.278	0.016	0.091
FX Carry	–0.087	0.294*	0.002	0.150	0.067	0.056	–0.922**	–0.240	–0.057	–0.229*
Interest Rate Trend	–0.036	–0.077	–0.242***	–0.153*	–0.172***	0.335	–0.418	1.056***	0.087***	0.658***
Interest Rate Carry	–0.328*	–0.172	–0.143**	–0.249***	–0.168***	0.742**	0.621*	0.901***	0.943***	0.803***
Interest Rate Vol. Carry	0.100	0.085	0.064	–0.026	0.074*	0.132	0.130	0.089	0.525**	0.192*
Interest Rate Curve	0.004	–0.073	–0.180*	–0.135	–0.167***	0.169	0.240	0.282	0.629**	0.402***
Interest Rate Value	–0.125	–0.056	–0.205***	–0.238***	–0.187***	0.334	0.825**	0.882***	0.694***	0.706***
Commodity Vol. Carry	0.100	0.206	0.211*	0.398***	0.229***	–0.051	–0.019	–0.236	–0.018	–0.070
Commodity Curve	–0.035	0.006	–0.111	–0.105	–0.078	–0.063	–0.084	0.181	0.106	0.056
Commodity Imbalance (1)	0.181	–0.014	–0.052	–0.106	–0.046	–0.152	0.138	0.512*	0.015	0.222
Commodity Imbalance (2)	–0.142	0.068	–0.058	0.211*	0.015	0.181	–0.165	–0.145	–0.343	–0.142
Commodity Trend	–0.191	0.037	–0.042	0.099	–0.009	0.245	–0.208	0.272	–0.163	0.051
Cross-Asset Trend	0.192	0.276*	–0.107*	0.014	0.012	0.298	–0.104	0.732***	0.499**	0.452***

Notes: This exhibit presents beta coefficients and t*-statistics obtained when risk premia strategy returns are regressed against global equity and bonds returns. MSCI World AC is used as the benchmark for global equity and Barclays Multiverse as the global bonds proxy. Beta estimation is based on monthly returns. *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% level, respectively.*

described in the second section, we calculate the indicator at the final trading day of each month using the macroeconomic data available at that point in time. According to the phase signaled by the regime indicator, the corresponding allocation scenario is selected. The considered ARP strategies receive either a long or a short signal.

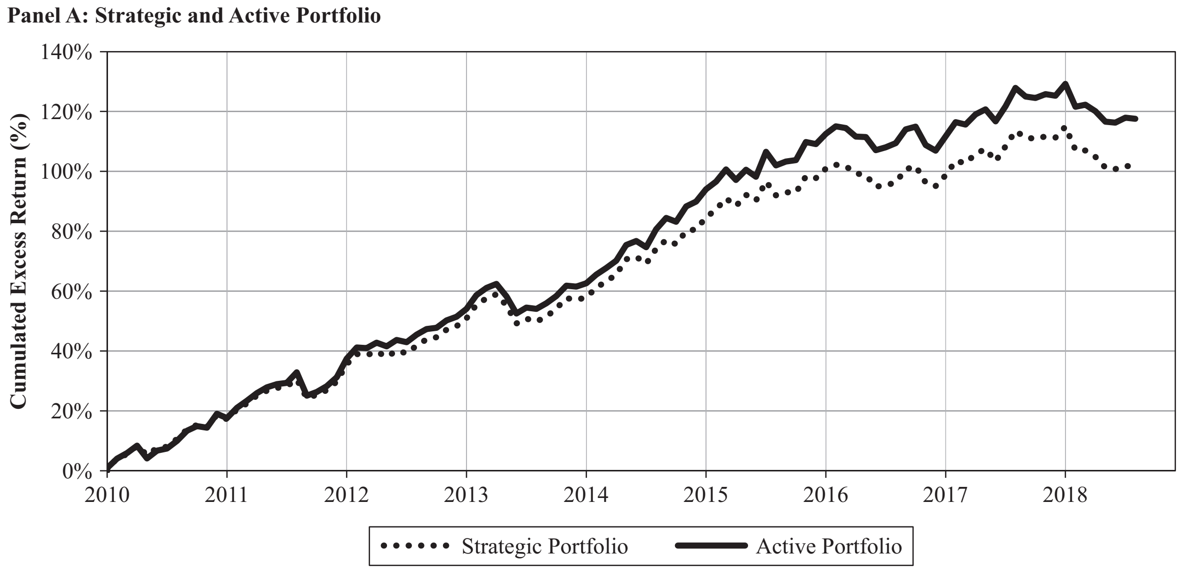
We implement the timing strategy as a tactical overlay portfolio. Hence, long/short positions are defined as over- and underweight positions relative to a strategic asset allocation. By combining the timing strategy with a risk parity approach, we measure explicitly the performance enhancement of intentionally deviating from an already risk optimized portfolio. The initial portfolio strategically allocates the 25 ARP strategies to contribute equally to the ex ante portfolio volatility of 5% p.a.[13]

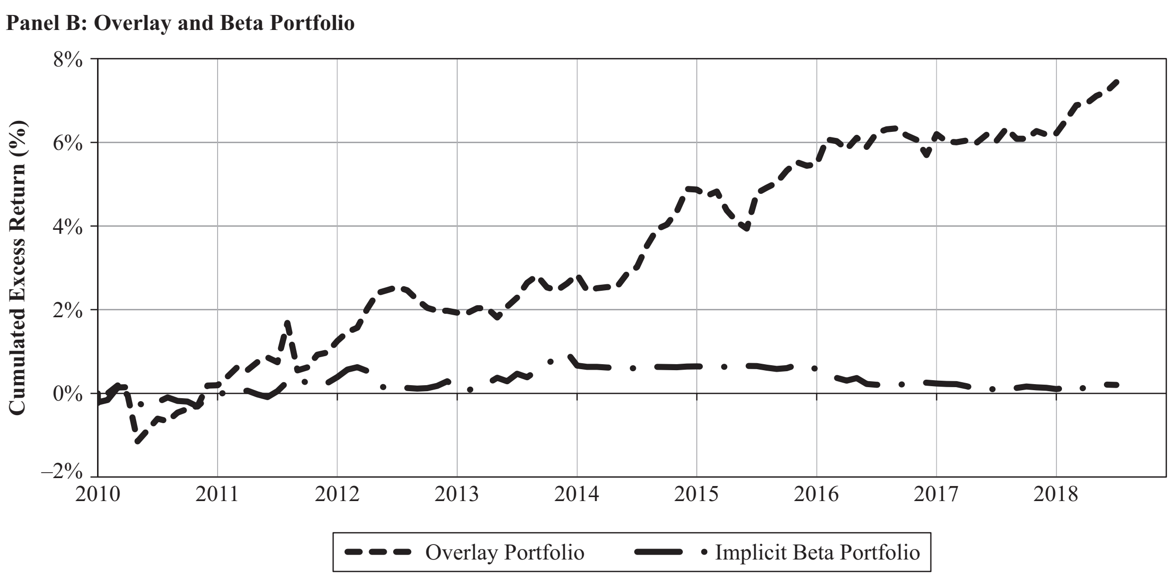
Finally, the tactical weights result from an optimization process with the tracking error target set at 1% p.a.

[13] The long-only risk parity portfolio can be subject to leverage.

Exhibit 5

Performance of Simulated Portfolios Based on ARP Strategies





Note: Monthly cumulated return data used from January 2010 to August 2018.

and the extent of the underweights being constrained by the strategic weights of considered ARP strategies. The calculated weights w^{TAA} define the dollar-neutral overlay portfolio for the upcoming period. We use an implementation lag of 1 trading day and rebalance the portfolio on a monthly basis. The output of this processing is a long/short portfolio that incorporates the conditional information assigned to the current market regime R. The daily return of the tactical overlay portfolio r^{TAA} is defined as follows:

$$r^{TAA} = \sum_{k=1}^{n} w_k^{TAA} * r_k, \text{ with } n \text{ being the number of ARP strategies considered.}$$

EXHIBIT 6
Performance Measurements of ARP Portfolios

	Strategic	Active (total)	Tactical (long/short)
Excess Return p.a.	8.20%	9.14%	0.82%
Volatility p.a.	5.61%	5.82%	0.94%
Sharpe Ratio	1.46	1.57	0.88
Max. Drawdown	8.6%	8.5%	1.6%
Value at Risk	–2.44%	–2.59%	–0.43%
Skewness	–0.69	–0.79	–0.88
t-Statistics	4.064***	4.246***	2.615***

Notes: Returns are net of transaction costs. Value at Risk is calculated for monthly return data on a 95% confidence level. t-*statistics pertain to the one-sided null hypotheses that mean portfolio returns are not above 0% using the Welch test. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.*

In the top chart of Exhibit 5, we graph the cumulated excess returns of the long-only risk parity portfolio with and without a tactical overlay. The bottom chart of Exhibit 5 displays the isolated performance of the tactical long/short portfolio. The reported performance data are net of transaction costs and calculated from January 2010 to August 2018 as we are limited as a result of the data availability of certain risk premia strategies. Further, we need 1 year of common data history to calculate the strategic weights of the risk parity portfolio and the ex ante volatility.

Exhibit 6 gives an overview of performance figures for the constructed portfolios. Applying a tactical overlay based on economic information increases the Sharpe ratio of the strategic portfolio further from 1.46 to 1.57. Investigating the tactical portfolio itself, the strategy achieves a consistent performance over the whole sample, generating a Sharpe ratio of 0.88. Observed returns are significantly positive according to the one-sided Welch test. To account for a non-Gaussian distribution of portfolio returns we further conduct the nonparametric Wilcoxon test, which leads to the same indication. The tactical portfolio had a period of weak performance from September 2012 to June 2014, recording its largest drawdown of 1.6%.

We further investigate the possibility of explaining observed conditional return patterns by underlying beta exposure. The importance of making the distinction between performance as a result of true alpha instead of implicit beta in the context of tactical asset allocation is also stressed by Lee (2000). If conditional beta exposure were the driving force behind identified patterns, then the approach would ultimately transform a factor timing strategy to a rather expensive beta timing strategy. To explore that possible explanation, we calculate the implicit strategy returns based on the regime-dependent betas (β_R^{EQ}, β_R^{FI}) reported in Exhibit 4. We use the return series and construct an implicit beta portfolio combining the implicit returns with the tactical weights w^{TAA} of the business cycle model. The daily return for the implicit beta portfolio r^{BETA} is defined as follows:

$$r^{BETA} = \sum_{k=1}^{n} w_k^{TAA} * (\beta_{k,R}^{EQ} * r^{EQ} + \beta_{k,R}^{FI} * r^{FI})$$

Assuming the conditional betas would perfectly explain observed strategy returns, explicit and implicit returns would be identical. However, as can easily be seen from the chart in Exhibit 5 returns of the implicit beta portfolio hardly distinguish from zero and return differences between both portfolios are significantly different from zero. On the basis of this analysis, we can exclude underlying beta exposure of actively allocated ARP strategies as an explanation for documented performance patterns.[14]

We are aware that we present only a short back-test horizon with few observations for each regime as we are limited by the available data history. In addition, several of the risk premia strategies have a major stack of back-tested data themselves. Therefore, having a somewhat idealized performance is not overly surprising. However, the major purpose of this article is not to implement a fully sophisticated portfolio timing strategy. We aim to give a realistic impression of macroeconomic sensitivities and the performance potential in exploring these dependencies in a tactical framework, considering a real investable set of risk premia strategies and rebalancing costs.

CROSS-VALIDATION

Calculated macroeconomic sensitivities and the derived allocation scenarios are based on the full sample because of data limitations. An approach based on in-sample strategy development followed by an out-of-sample

[14] We further extend the multivariate regression by adding commodity returns as explanatory variables. However, as conditional betas have only a marginal effect on implicit strategy returns, we withdraw from reporting the results.

EXHIBIT 7
Conditional Excess Return of Multi-Asset Strategies

	Annualized Excess Return in %					ANOVA		
Multi-Asset Strategy	**Expansion**	**Peak**	**Recession**	**Recovery**	**Overall**	**Obs.**	***F*-Statistics**	***p* Value**
Equity North America	14.55	3.87	–19.76	16.37	3.81	199	11.666	<0.001***
Trading Signal	+1	+1	–1	+1				
Equity Europe	12.95	7.28	–24.50	16.19	2.73	199	12.761	<0.001***
Trading Signal	+1	+1	–1	+1				
Equity Japan	16.59	–2.07	–19.37	13.42	2.30	199	10.722	0.002***
Trading Signal	+1	–1	–1	0				
Equity Pacific ex Japan	16.68	9.31	–17.49	18.17	6.55	199	7.657	0.007***
Trading Signal	+1	+1	–1	+1				
Equity Emerging Mkts.	21.40	8.24	–19.53	17.67	6.84	199	8.068	0.006***
Trading Signal	+1	+1	–1	+1				
Global Treasuries	1.12	2.46	4.98	1.62	2.32	199	3.164	0.078*
Trading Signal	–1	–1	+1	–1				
Global Credit	1.99	1.29	1.62	6.56	2.86	199	4.606	0.034**
Trading Signal	–1	–1	+1	–1				
Securitized	1.30	1.00	3.97	3.64	2.35	199	2.541	0.114
Trading Signal	–1	–1	+1	–1				
Global High Yield	5.84	3.41	–5.15	21.30	6.42	199	10.776	0.001***
Trading Signal	–1	0	0	+1				
Gold	7.40	6.53	16.80	–3.03	5.90	199	1.980	0.163
Trading Signal	0	+1	+1	–1				
Inflation-Linked Bonds	3.39	1.81	5.05	3.51	3.31	199	0.572	0.451
Trading Signal	–1	–1	+1	–1				

*Notes: Mkts. = markets; obs. = number of monthly observations given for the data sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.*

test is practically infeasible as the number of observations per regime is relatively small. In applying a data-splitting approach, the in-sample set would already require most of our available sample, leaving hardly any remaining data for an out-of-sample test. In an attempt to validate our previous findings without having sufficient data history, we repeat the described procedure using global multi-asset classes and style factors to compare results with idealized asset behavior, on the one hand and, on the other hand, to examine the predictive power of the business cycle model given a different set of investments.

Global Multi-Asset Classes

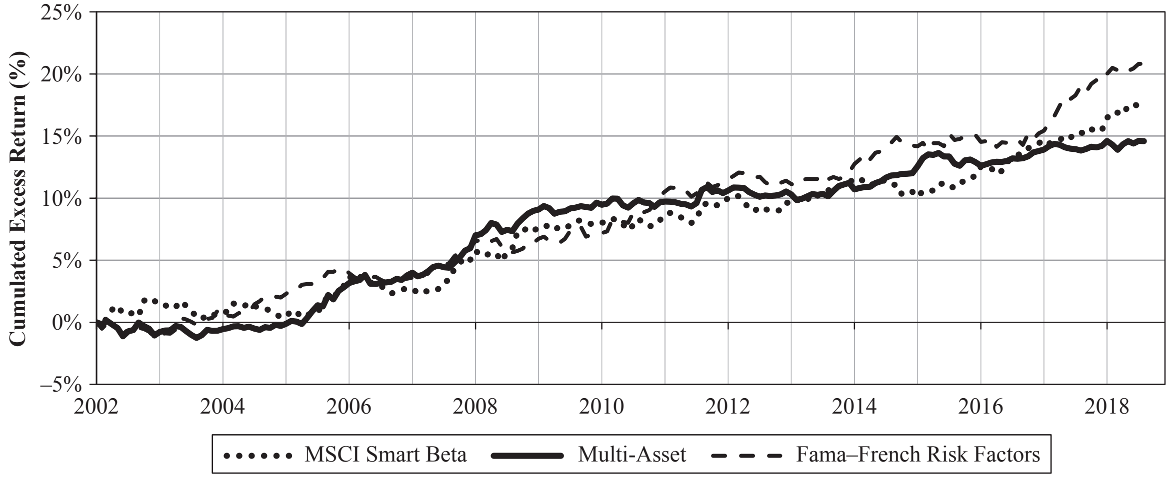
First, just as we did with risk premia strategies, we investigate the conditional performance of regarded multi-asset classes. Results are reported in Exhibit 7. In line with the assumptions we have made, equities have strong differences in conditional excess returns. Performance in expansion and particularly in the recovery phase is highly positive, whereas the opposite is true in recession. There is a considerable drop in returns for equities in the peak phase compared with the expansion phase. Although most of the conditional equity performance in the peak phase remains positive, an expected increase in dispersion can be observed.[15] Documented results are highly significant at the 1% level.

Findings for the bond market are equally strong with global Treasuries outperforming in recession while underperforming in expansion, an economic environment of steady growth and rate hike anticipation (Ludvigson and Ng 2009). In regard to the regime-related return differences between Global High Yield and Global Credit, results match the conditional performance of the Credit Carry premium strategy. Although the return difference and the strategy

[15] Results for regime-related volatility are not reported here.

EXHIBIT 8

Performance of Long/Short Portfolios Based on Multi-Asset Classes and Equity Style Factors



Note: Monthly cumulated return data used from January 2002 to August 2018.

performance are especially positive in the recovery and expansion phases, Global High Yield relatively underperforms in recession, when investors likely look to diminish default risks (see Exhibits 3 and 7). In addition, safe-haven assets Gold and inflation-linked Bonds perform best in recession, when the demand from market participants for risk-averse assets is peaking.

However, although return patterns for Gold fit the expectation, results are not statistically significant. This finding might be partially explained by the temporary indication of a recession in the context of the dotcom crisis in the early 2000s. Although equity markets were hit, this was not an idealized type of recession in which inflation and unemployment typically pick up while growth expectations decrease. Hence, the markets demand for Gold was rather low and so was the conditional return during this period.

Finally, we construct a long/short portfolio using a straight quantitative approach to set up allocation scenarios for the traditional multi-asset classes. We rank the assets according to the conditional excess returns and form the phase-related portfolios accordingly (see Exhibit 7). It is noteworthy that although most of the constructed allocation scenarios fit the economic intuition of conditional asset behavior, we acknowledge that the resulting allocation scenario of the peak phase is biased on the data sample used. Assuming that the return of equities will eventually decline with progressing duration of the economic slowdown, the origin of any global recession remains dynamic. Therefore, relying solely on the observed return patterns, particularly in this regime, is not recommended for practical application.

The reported performance is calculated from January 2002 to August 2018. We graph cumulated excess returns of the timing strategy as the bold line in Exhibit 8. The active strategy has a consistent active performance over the whole sample, generating a Sharpe ratio of 0.79 without transaction costs.

We withdraw from accounting for costs as most of the assets can be traded at single digit basis points nowadays. In any case, the impact on the overall performance should be rather low at a two-way turnover of only 68% p.a. The portfolio had a long period of flat performance from October 2002 to May 2005 as inconclusive signaling from the economic regime indicator in the aftermath of the mentioned dotcom crisis affected the active performance. Maximum drawdown was at 1.6% for an ex ante portfolio volatility of 1% p.a.

Equity Style Factors

In Panel A of Exhibit 9, we report the active performance of MSCI smart beta style indexes conditional on each economic regime. During the expansion phase, well-established investment trends in equity markets tend to support momentum stocks. Typically, only a small share of the overall stocks accounts for most of the market's performance as the economy reaches its

Exhibit 9
Conditional Sharpe Ratio of Equity Style Factors

	Annualized Sharpe Ratio					ANOVA		
Equity Style Factor	**Expansion**	**Peak**	**Recession**	**Recovery**	**Overall**	**Obs.**	***F*-Statistics**	***p* Value**
Panel A: MSCI World Smart Beta Style Indexes								
Momentum	0.75	1.26	–0.34	0.54	0.32	199	0.774	0.510
Trading Signal	+1	+1	–1	0				
Size	0.47	0.17	0.09	1.06	0.34	199	2.680	0.048**
Trading Signal	0	–1	0	+1				
Value	1.57	–0.31	–0.30	0.94	0.47	199	1.957	0.122
Trading Signal	+1	–1	–1	+1				
Quality	–0.37	1.30	0.58	0.13	0.34	199	3.303	0.021**
Trading Signal	–1	+1	+1	–1				
Minimum Volatility	–0.33	0.38	0.40	–0.22	0.11	199	1.438	0.233
Trading Signal	–1	0	+1	–1				
Panel B: Fama–French Five Factors								
MKT	1.50	0.71	–0.71	1.81	0.48	199	4.746	0.003***
Trading Signal	+1	+1	–1	+1				
SMB	0.28	–0.29	0.15	1.18	0.34	199	1.430	0.235
Trading Signal	–1	0	0	0				
HML	0.48	–0.51	–0.64	0.79	0.04	199	2.197	0.090*
Trading Signal	+1	–1	–1	–1				
RMW	0.46	0.13	0.99	0.13	0.43	199	0.983	0.402
Trading Signal	0	+1	+1	–1				
CMA	–0.62	–0.66	0.39	1.61	0.26	199	5.364	0.001***
Trading Signal	–1	–1	+1	+1				

*Notes: Obs. = number of monthly observations given for the data sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.*

turning point (Bessembinder 2018). In the peak phase, this mechanism seems to intensify as the outperformance of momentum stocks is increasing even further.

However, a growing sense of risk awareness among market participants might be responsible for minimum volatility and quality strategies having above-average returns in the peak phase as well, with the economic development starting to slow down (Ang et al. 2006). This trend continues in recessions, when the economy is exposed to different types of shocks. Investors' demand is high for crisis-proof assets, and companies with relatively low leverage, stable earnings, and high profitability (RMW) might be favored (Hodges et al. 2017). Finally, when the economy recovers from its trough, size and value strategies witness the highest relative performance, with Sharpe ratios at about one.

Although, besides fitting economic intuition, reported results for momentum are statistically nonsignificant (Chordia and Shivakumar 2002).[16] Noisy performance might explain that effect, particularly in recovery and recession phases. Momentum strategies suffer most from swift changes in investment trends typically occurring in these regimes (Daniel and Moskowitz 2016). That leads to a temporary underperformance, but with an extending duration of the prevailing regime, the strategy will eventually adjust its allocation, and so will the conditional performance.

[16] Conditional performance of the momentum-style factor shows little conformity with return patterns of the Equity Trend strategy (see Exhibits 3 and 7). Although insignificant, this can be at least partially attributed to the diverging investment style. The momentum factor selects past winners versus past losers on the single-stock level; in contrast, the Equity Trend strategy operates on the index level.

EXHIBIT 10
Performance Measurements of Long/Short Portfolios

	Multi-Asset	MSCI Smart Beta	Fama–French Risk Factors
Excess Return p.a.	0.80%	0.94%	1.07%
Volatility p.a.	1.01%	1.03%	1.24%
Sharpe Ratio	0.79	0.91	0.86
Max. Drawdown	1.6%	2.1%	2.2%
Value at Risk	–0.35%	–0.41%	–0.42%
Skewness	0.20	0.59	–0.03
t-Statistics	3.598***	3.362***	4.292***

Notes: Value at Risk is calculated for monthly return data on a 95% confidence level. t*-statistics pertain to the one-sided null hypotheses that mean portfolio returns are not above 0% using the Welch test. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.*

Observed return patterns for size and value can be validated with the equivalent SMB and HML factors defined by Fama–French. Compliant with the conditional active performance of the MSCI smart beta indexes, both factors record below-average Sharpe ratios in the peak phase as well as in recession while being highest in recovery (Panel B of Exhibit 9). Stocks with a conservative investment policy seem to underperform when risk appetite is high, as in expansion. With investors rather cautious in recession and maybe still cautious in the recovery phase, low investment companies tend to be relatively attractive in these regimes.

The regime-related extent of the equity premium (MKT) delivers supporting evidence for the conditional attractiveness of global equities reported in the prior section. Our findings are very nearly in line with the economic regime–related factor returns analyzed in previous studies (e.g., Amenc, Goltz, and Lodh 2018). However, observed return differences are significant for only half of the considered equity style factors. With the sample being rather short because of restrictions for the macroeconomic data, evidence for the timing capability of equity style factors remains scarce. In particular, the time-varying relationship between indicators and factors and the existence of temporary investment trends make a dynamic approach a necessity (Bender et al. 2018). Therefore, the general application for active allocation and interpretation of equity style factors is less straightforward as for much of the considered ARP strategies.

We use the reported regime-related performance to set up allocation scenarios for both sets of equity style premia. When active performance is back-tested according to the methodology already used for the multi-asset classes, both timing portfolios record highly positive Sharpe ratios at 0.91 and 0.86, respectively, using the MSCI smart beta indexes and Fama–French risk factors (see Exhibit 10). The reported performance is gross of all transaction costs and calculated from January 2002 to August 2018 for an ex ante volatility of 1% p.a. Cumulated returns of both long/short portfolios are illustrated as dotted and dashed lines in Exhibit 8. According to Exhibit 10 maximum drawdowns were at 2.1% and 2.2%.

CONCLUSION

By analyzing macroeconomic sensitivities, we show that time-varying returns of ARP strategies are significantly related to economic conditions. Our results are distinguished from the findings made by Ilmanen, Maloney, and Ross (2014). The discrepancy can be at least partially explained by the composition of analyzed strategies. We construct long/short-style premia strategies by combining different asset classes. However, as the strategies' performance is at least to some degree assumed to be related to the underlying asset behavior, and with asset classes not being perfectly correlated, it is in line with expectations that differences in regime-related aggregate returns are insignificant. To increase the probability of identifying meaningful return patterns we analyze macroeconomic sensitivities of asset class–specific ARP strategies. On the basis of our findings, we select strategies and construct a timing portfolio that illustrates the return potential of a regime-related allocation approach.

As transaction costs for ARP strategies remain relatively high compared with traditional asset classes, using a timing strategy with a low frequency of trading signals is preferable. In contrast to many other proposed active investment strategies with reported high Sharpe ratios but also high turnover, our business cycle model achieves a trade-off between signal frequency and reactiveness to changing economic circumstances.

Given the real data set of tradable ARP strategies and the accounting of transaction costs, the calculated performance of the active portfolio gives at least a realistic impression of the possible profitability of using factor timing as a tactical overlay. To test the hit ratio of our business cycle model we investigate the conditional returns of different asset classes and style factors. Results are in line with theoretical assumptions and the findings of previous studies (e.g., Hodges et al. 2017, Blin et al. 2018).

With our given look-back period being relatively short because of data limitations, further research analyzing different data sets of ARP with an extended history to validate our findings might be necessary.

However, because the underlying causal links might be time-varying, a dynamic approach to select macroeconomic data for predicting the business cycle and to control for adjustments in sensitivities of ARP strategies is a must. Therefore, future studies might focus on developing models capable of grasping the ever-changing structural macroeconomic environment in selecting explanatory data in a continuous approach.

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ADDITIONAL READING

Mind the Gap: *On the Importance of Understanding and Controlling Market Risk in Smart Beta Strategies*
Noël Amenc, Felix Goltz, and Ashish Lodh
The Journal of Portfolio Management
https://jpm.pm-research.com/content/44/4/60

ABSTRACT: *The authors argue that more attention should be paid to market exposure when conducting analyses of smart beta strategies. They point out that most research proposing new multifactor investment methodologies essentially ignores exposure to the market factor, which is the most consensual among all factors and often the most influential factor for a strategy. Overlooking the dominant factor is in stark contrast to the objective of factor investing, which aims to identify and manage the main drivers of risk and return. The authors document that different levels of market beta indeed have a strong impact on the performance and risk of smart beta strategies. The impact is visible in terms of long-term returns, volatility, and the dependence of performance on market conditions. Such effects need to be properly documented to allow investors to make explicit choices in their risk exposures. In the event of a mismatch with investor preferences, it is possible to adjust multifactor strategies to respect target levels of market beta.*

The Credit Risk Premium
Attakrit Asvanunt and Scott Richardson
The Journal of Fixed Income
https://jfi.pm-research.com/content/26/3/6
ABSTRACT: *Despite theoretical and intuitive reasons for a credit risk premium, past research has found little supporting empirical evidence. This is primarily attributable to biases in computing credit excess returns, which improperly account for term risk. Using data spanning 80 years in the United States and nearly 20 years in Europe, the authors find strong evidence of a credit risk premium after correctly adjusting for term risk. The credit risk premium is not spanned by other known risk premia, and it exhibits time variation related to economic growth and aggregate default rates. These results have important implications for asset pricing and investment decisions.*

The Promises and Pitfalls of Factor Timing
Jennifer Bender, Xiaole Sun, Ric Thomas, and Volodymyr Zdorovtsov
The Journal of Portfolio Management
https://jpm.pm-research.com/content/44/4/79

ABSTRACT: *The potential to dynamically allocate across factors, or* factor timing, *has been an area of academic and practitioner research for decades. In this article, the authors revisit the promises of factor timing, documenting the historical linkages between equity factor performance and different groupings of predictors: sentiment, valuation, trend, economic conditions, and financial conditions. The authors highlight that different predictors are more relevant for certain horizons, so the horizon is critical in factor timing. They also argue there are significant pitfalls with factor timing as well. The difficulty of timing factors has been well documented, given the uncertainty of exogenous elements affecting their behavior and the complexity of the underlying relationships. Most importantly, the underlying causal links are time varying. In addition, these relationships are observed with the benefit of hindsight and thus suffer from the age-old problem of data mining. Despite these caveats, the authors believe that at the margin it is possible to time certain elements that can add value and improve outcomes.*