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Methods in Dynamic Weighting
Incorporating market and security level context into your investment process

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The bread and butter for quantitative portfolio managers has traditionally been static multifactor models. These models have provided *fairly* consistent performance especially in stable market environments. However, they have weathered their fair share of storms where a certain style or strategy underperforms for a prolonged period. Mitigating these episodes of relative underperformance would enhance almost any quantitative investment process, but relating broad market and time series dynamics to individual security selection is a challenging proposition.

In this report, we introduce a powerful discovery tool in Alphaworks and provide a pragmatic survey covering the identification and potential dynamic techniques to handle financial regimes and security level context. With increasingly volatile factor performance, the ability to implement adaptive strategies is paramount in maximizing factor efficacy. Our work provides the following insights:

- Leveraging the Alphaworks Regime Monitor, we provide a simple case study showing that up/down markets favor different factors (value in down markets/momentum in up markets). This illustrates that regimes can have a real impact on the relative efficacy of common factors in an investment process.

- Dynamically weighted **Factor Momentum** strategies, utilizing the trailing performance of competing signals, produce a higher mean monthly return and higher Annualized IR compared to an equal weight benchmark that ignores historical performance.

- A dynamic weighting strategy using **Factor Spreads** as a potential indicator for future return dispersion (opportunity) yields a higher mean monthly return and higher annualized IR compared to an equal weight benchmark.

- Simple **Macro Regression** incorporating changing market level dynamics to predict future relative performance provides underwhelming guidance. We obtain results that are strong in-sample but weak out-of-sample.

- Modeling regime characteristics of a time series using a **Hidden Markov Model** identifies regimes, provides estimates of the current regime, and predicts probabilities of forward regimes. Incorporating these estimates from a time series of relative factor performance to dynamically weight a model yields larger T-Stats for monthly IC and wider Top-Bottom Spreads.

- **Contextual Modeling** blends two models that have been developed to reflect differences in factor efficacy along an independent risk context. For example, high and low growth stocks should apply different model weights on different factors. We show that models with optimized factors weights based on historic performance and context outperform an equal weight benchmark in IR space but perform similarly to a "no context" model that simply optimizes weights for the entire universe.

1 Regime Identification and Impact

Regimes can broadly be defined as complementary periods that fundamentally differ in some way. Many regimes arise naturally such as Recession/Recovery, High/Low Volatility, Rising/Falling Sentiment and Political/Regulatory periods. We believe that taking these types of regimes into consideration is important in the investment process as factor payoffs vary widely depending on current market conditions.

We conducted a preliminary study on the potential impact of regimes on factor performance. The most intuitive market regime may simply be up vs. down markets. A cursory pass using the Alphaworks Regime Monitor shows drastically varied factor performance given the market environment, Figure 1.

Figure 1: Up/Down Markets Using the Alphaworks Regime Monitor
Russell 3000, From 1990

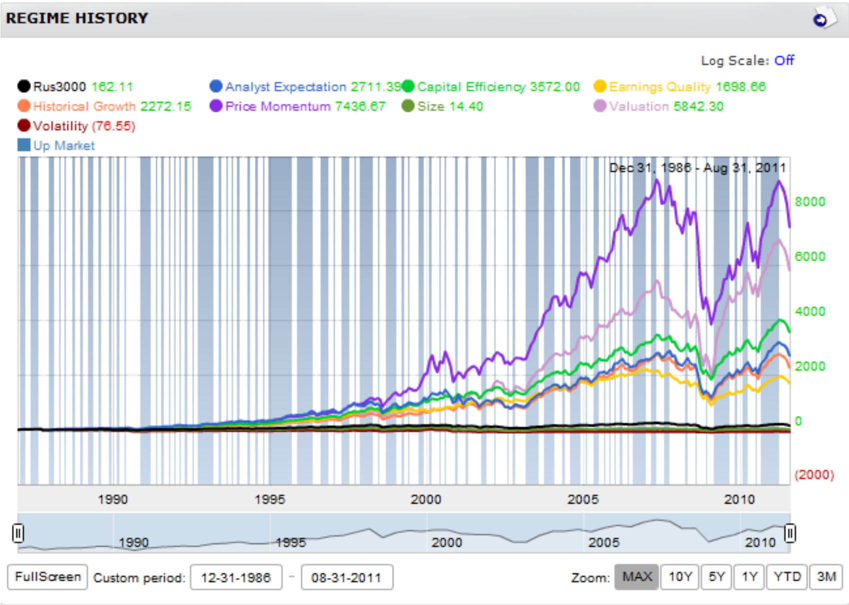
Regime Monitor

FACTOR SEARCH

Market Snapshot \ What's Working \ Quant Calendar \ Regime Monitor \ Monthly Report

Training

REGIME: Up Market / Down Market INDEX: Russell 3000 TIME PERIOD: From 1990



Summary | Calendar | Description

Regime Summary From 1990:

	Up Mkt	Down Mkt
Current Regime		4 months
# of Regimes	62	62
# of Months	161	100
% of History	61.69%	38.31%
Avg Duration	2.60	1.61
Longest Run	10	5
Begin	Dec 1994	Multiple
End	Sep 1995	Multiple
Shortest Run	1	1
Begin	Multiple	Multiple
End	Multiple	Multiple
Index Summary		
Avg Cap Wgt Rtn	4.07%	(2.94)%
Avg Eq. Wgt Rtn	3.69%	(4.70)%
Max 1 Month Rtn	20.12%	7.98%
Min 1 Month Rtn	(2.82)%	(23.08)%
% of Up Mkt	90.06%	11.00%
% of Down Mkt	9.94%	89.00%

Summary | Current v. Hist

Display: Style Composites Order: Top Sector: Cross Sectional Portfolio: Absolute Return

Up Market

Style	Factor	Q1	Q5	Sprd% ▾	Ann Sprd%	Q1 Hit	Q5 Hit	Avg IC	Best IC	Worst IC	IC T-Stat	%Pos IC
Vol	Volatility	6.39	2.36	4.03	60.72	81.88	90.63	0.05	0.50	(0.36)	4.38	64.38
PM	Price Momentum	5.48	3.36	2.12	28.66	95.00	73.75	0.06	0.32	(0.28)	7.56	78.75
AE	Analyst Expectation	5.21	3.76	1.45	18.87	91.88	86.25	0.04	0.22	(0.22)	5.82	70.63
Sz	Size	4.39	3.64	0.76	9.45	83.75	96.88	(0.02)	0.33	(0.29)	(2.81)	38.75
HG	Historical Growth	4.71	4.64	0.08	0.90	92.50	85.00	0.02	0.18	(0.19)	4.63	70.63
Val	Valuation	4.71	4.95	(0.24)	(2.83)	92.50	81.25	0.02	0.23	(0.31)	2.73	58.13
CE	Capital Efficiency	4.14	4.58	(0.44)	(5.15)	95.00	80.00	0.02	0.22	(0.28)	3.06	63.75
EQ	Earnings Quality	3.43	4.42	(0.99)	(11.25)	92.50	81.25	(0.00)	0.25	(0.22)	(0.55)	45.63

Down Market

Style	Factor	Q1	Q5	Sprd% ▾	Ann Sprd%	Q1 Hit	Q5 Hit	Avg IC	Best IC	Worst IC	IC T-Stat	%Pos IC
Val	Valuation	(3.11)	(8.35)	5.24	84.63	22.00	11.00	0.11	0.46	(0.13)	8.56	80.00
CE	Capital Efficiency	(3.12)	(7.98)	4.86	76.80	22.00	10.00	0.10	0.34	(0.12)	10.96	87.00
EQ	Earnings Quality	(2.71)	(7.21)	4.50	69.52	17.00	13.00	0.10	0.34	(0.11)	10.08	83.00
HG	Historical Growth	(4.19)	(7.14)	2.95	41.79	17.00	9.00	0.05	0.24	(0.17)	6.07	72.00
PM	Price Momentum	(4.28)	(6.68)	2.40	32.88	21.00	9.00	0.05	0.37	(0.20)	5.17	73.00
AE	Analyst Expectation	(4.84)	(4.53)	(0.32)	(3.72)	17.00	11.00	(0.01)	0.25	(0.23)	(1.11)	48.00
Sz	Size	(6.01)	(3.47)	(2.54)	(26.54)	18.00	10.00	(0.07)	0.28	(0.31)	(5.58)	27.00
Vol	Volatility	(9.45)	(1.38)	(8.06)	(63.53)	10.00	31.00	(0.21)	0.29	(0.63)	(12.56)	9.00

As shown in Figure 1, the historical data paints a logical picture. Volatility, Price Momentum, and Analyst Expectations outperform in Up Markets when investors are looking for growth opportunities, while Value, Capital Efficiency, and Earnings Quality lead in Down Markets when investors are flocking to safe investments. This, however, is just an explanation of what type of factors out- and under perform in a specific regime. As the regimes in Alphaworks are defined with hindsight, it is not an ex-ante forecast of what factors will outperform in the future based on a known regime.

We define three natural categories for regimes in Alphaworks (out of a library of 37 pre-defined regimes), Market Regimes (High/Low Volatility), Economic Regimes (High/Low Unemployment), and Calendar Regimes (Republican/Democratic President). The standard regime library should provide a good base for many investors. The Regime Monitor is also flexible enough to handle custom regimes. If you can effectively bisect the time period, you can get a quick look at how our factor library performed in your own regimes.

Selecting appropriate regimes depends on identifying mutually exclusive states that are recurrent, are reasonably predictable, and yield contrasting factor performance across regimes. This may not seem like a considerable challenge, but there are many intuitive choices that fail to meet these criteria for a variety of reasons. Regime transitions may occur too infrequently, occur too frequently, not induce dramatic performance differences, or simply be too difficult to predict with sufficient accuracy. While the Regime Monitor is a good first step for regime identification, further research is needed to determine the viability of a regime in an investment process.

2 Dynamic Strategies

We have shown that regimes can have an appreciable impact on factor and portfolio performance Executing strategies that incorporate forecasts of future regimes or are sufficiently adaptive should yield fruitful results. The following sections discuss several methods of dynamic modeling intended to assuage the impact of changing market dynamics on portfolio performance. The techniques outlined represent practical and promising approaches to incorporating regimes into an investment process.

As this is intended as more of a technical survey, we focus primarily on modeling regimes of relative factor performance. This time series can easily be decomposed into binary regimes, switches with regularity, and ensures varied performance (defined as one factor outperforming the other). We define relative performance as the spread of the individual factor equal weight top-bottom quintile spreads.

$$Spread\ of\ Spreads = (Q1\ Return_{EP} - Q5\ Return_{EP}) - (Q1 Return_{PMOM} - Q5\ Return_{PMOM})$$

Specifically, we chose to study Earnings to Price (EP) and 12 Month – 1 Month Price Momentum (12M1M) as simple proxies for popular Value and Momentum strategies. These are often viewed as opposing strategies. This relationship is discussed further in our *July 2011 – Research Briefs*. As such, they are natural candidates for a dynamic strategy. We test our switching strategies by constructing two factor models that employ dynamic weights and compare to an equal weight benchmark.

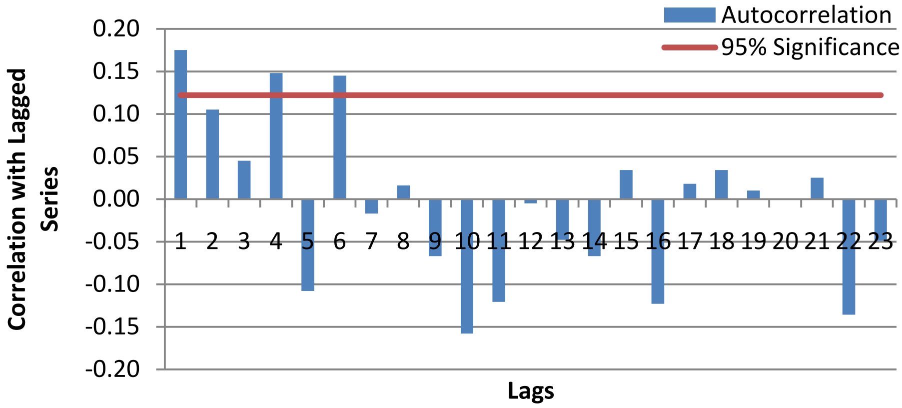
FACTOR MOMENTUM

The motivation for our first strategy is to exploit any persistence in relative performance or monthly factor loadings for our two factors. This approach is appealing due to its intuitive nature and relative ease of implementation. We begin by testing the persistence of the spread of spreads formally by looking at the autocorrelation of this time series, Figure 2.

Significant AR's are observed in the spread of spreads at 1 month, 4 months, and 6 months. This indicates that there may be sufficient persistence in the relative factor performance to derive a switching signal from their trailing returns. Three switching signals were constructed utilizing different trailing information horizons for short, medium, and long term persistence.

We find significant autocorrelation in relative performance at 1 month, 4 months, and 6 months. This persistence is used to construct a dynamic weighting signal.

Figure 2: Autocorrelation of Spread of Spreads
Russell 3000, 1/31/1991 to 6/30/2011



We take the 1 month, 6 month, and 12 month simple moving average of the spread of spreads as our switching signal. This shows on average which of our signals has outperformed in the trailing periods. The sign of this trailing average gives us the prediction for which factor to overweight in our investment process (positive=Value/negative=Momentum). The strength of these signals is evaluated by testing their hit rate of predictions, Table 1.

$$Hit\ Rate\ of\ Predictions = \frac{\#\ of\ Correctly\ Predicted\ Periods}{\#\ of\ Periods}$$

While all three signals have hit rates greater than 50%, only the 6 month signal is significantly different than 50% at the 95% confidence level using an exact binomial test.

Table 1: Factor Momentum Hit Rate
Russell 3000, 1/31/1991 to 6/30/2011

	1 Month	6 Month	12 Month
Hit Rate	52%	57%**	54%

The 6 month signal is then incorporated into two models to dictate which factor to overweight. The first is a "fixed tilt" where we overweight the factor predicted to outperform ($Factor_{out}$) as 80% of the model. The second is an "informed tilt" which uses the ratio of average ICs in periods where we predicted the same factor to outperform (e.g. all periods in the past where $Factor_{out}$ = EP). $Factor_{out}$ is determined using the sign of the 6 month trailing performance signal as outlined previously.

$$Fixed\ Tilt = .8(Factor_{out}) + .2(Factor_{under})$$

$$Informed\ Tilt = \frac{Avg\ IC_{out}}{Avg\ IC_{under}}(Factor_{out}) + \frac{Avg\ IC_{under}}{Avg\ IC_{out}}(Factor_{under})$$

We backtest these two strategies and our equal weight benchmark in the Russell 3000 from January 1991 to June 2011. The results from these backtests are outlined below, Table 2.

Table 2: Factor Momentum Monthly Performance – Trailing Performance Signal
Russell 3000, 1/31/1991 to 6/30/2011

	Equal Weight	Fixed Tilt	Informed Tilt
Avg 1 Month Spread	1.08%	1.27%	1.17%
Annualized IR	.44	.65	.56
Avg 1 Month IC	.052	.053	.051

We find the simple equal weight model performs fairly well in this period. However, both of our models incorporating the 6 month switching signal outperform the equal weight benchmark in return space, although we do not find the difference significant at the 90% level.

We also tested a regression based methodology to obtain a dynamic weight factor momentum strategy. We conducted cross-sectional regressions each month using our alpha factors to predict one month forward returns. If a factor had a non-significant T-stat in a given period, the coefficient for that period is set to zero. The six month moving average of our regression coefficients lagged one month is then used as factor weights.

To ensure the regression coefficients are comparable in scale and to mitigate the effect of outliers, we applied the following transformation: the variables were ranked and then subsequently transformed into a standard normal distribution. This also has the beneficial effect of giving more importance to observations in the tails since in practice portfolios are formed by stocks in the tails. These backtest results are outlined below, Table 3.

Table 3: Factor Momentum Monthly Performance - Regression Method
Russell 3000, 1/31/1991 to 6/30/2011

	Equal Wt	Reg. Rank	Reg. Norm.
Avg 1 Month Spread	1.08%	0.95%	1.32%
Annualized IR	.44	.48	.65
Avg 1 Month IC	.052	.053	.049

In terms of top bottom spreads, the regression method using normalized factors outperforms the rank regression and equal weight. We also experimented with t-stats of the factor coefficients as factor weights, to penalize the coefficients associated with larger variance. We found these results to be comparable to our previous factor weights. As in the simple momentum, we don't find the performance difference to be significantly different at the 90% level.

FACTOR SPREADS

We believe factor value spreads may be indicative of future return dispersion (opportunity). We find current spreads in our EP factor to be correlated with future return and IC performance.

According to the Grinhold and Kahn fundamental law, portfolio performance is related to the skill and breadth of the investment process. However, differentiated, realized performance measured over short intervals is heavily influenced by the dispersion of security returns (opportunity) (Asness 1997). There is no room to highlight superior skill if the period returns act homogenously. We hypothesize that factor spreads may be a potential proxy for forward return dispersion. Therefore, a factor should have higher potential payoffs in periods when there is a wide spread in raw factor values. Our factor spreads compare the median factor value in our top and bottom deciles. Forward factor performance is measured in terms of both IC and returns. Table 4 details the relationships between these series.

Table 4: Correlation Matrix of Factor Spread and 3 Month Forward Performance
Russell 3000, 1/31/1991 to 6/30/2011

	EP spread	PMOM spread	EP Return	PMOM Return	EP IC	PMOM IC
EP spread	1.00	0.62	0.14	(0.07)	0.18	(0.17)
PMOM spread	0.62	1.00	(0.02)	0.16	0.04	0.03
EP Return	0.14	(0.02)	1.00	(0.56)	0.85	(0.47)
PMOM Return	(0.07)	0.16	(0.56)	1.00	(0.35)	0.90
EP IC	0.18	0.04	0.85	(0.35)	1.00	(0.35)
PMOM IC	(0.17)	0.03	(0.47)	0.90	(0.35)	1.00

We find positive correlations between our factor spreads and 3 month forward long-short spread return and IC. This approach seems most promising with EP as we see a relationship in both return and IC space. We ran regressions for both of the 3 month forward performance measures and find significant coefficients for the EP spread, Table 5.

Table 5: Regression Analysis of Factor Spread and Forward Performance
Russell 3000, 1/31/1991 to 6/30/2011

	3 MO EP Return Regression			3 MO EP IC Regression		
	Intercept	**EP Spread**	**R-Squared**	**Intercept**	**EP Spread**	**R-Squared**
	-0.04231	0.0047	0.0260	-0.0283	0.0053	0.0296
T-Stats	(-1.89)	(2.54)		(-1.21)	(2.72)	

These results prompted an attempt to incorporate factor spreads into an investment process. Our investment thesis is that factors believed to have large opportunity sets should be overweight accordingly. Therefore, factors with wide spreads in the current period should be emphasized in an investment process.

We constructed a model that highlights EP when we observe a wide factor spread. The level of the current spread is compared to its historic average every period on an expanding basis. We assign our fixed value tilt if the spread is greater than one standard deviation above the historic mean. Otherwise, we assign our neutral equal weight model.

We backtest this dynamic strategy and compare to our equal weight benchmark in the Russell 3000 from January 1991 to June 2011. The results from these backtests are outlined below, Table 6.

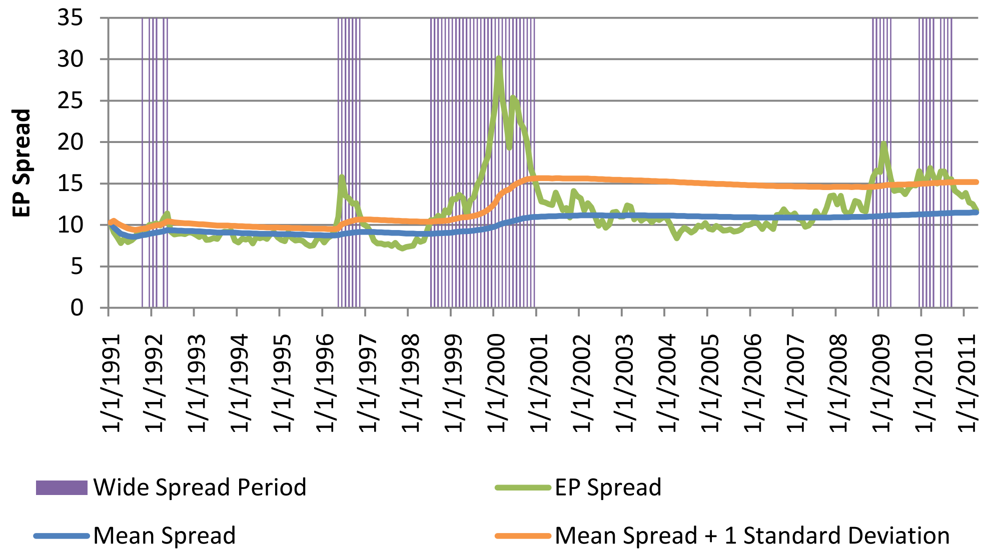
Table 6: Factor Spread Monthly Performance
Russell 3000, 1/31/1991 to 6/30/2011

	Equal Weight	Fixed Tilt
Avg 1 Month Top Bottom	1.08%	1.14%
Annualized IR	.44	.52
Avg 1 Month IC	.052	.053

The dynamic model essentially mimics the neutral strategy for significant stretches in our period, but it identifies enough periods to add value, Figure 3.

Unfortunately, we do not find the differences to be statistically significant at the 90% level. Even so, we feel the initial results are promising and generally consistent with our investment thesis. There seems to be a logical relationship between factor dispersion and forward performance.

Figure 3: Factor Spread and Period Classification
Russell 3000, 1/31/1990 to 6/30/2011



MACRO REGRESSION

The systematic influence of macroeconomic and capital market factors on stock market returns has intrigued researchers and practitioners alike for years. Unfortunately, the results have been generally lack-luster. Clearly, it is difficult to use aggregate or tangential factors to make stock specific decisions. In recent years, the high level of volatility at the macro level has influenced general equity portfolio performance. Whether to maximize returns or mitigate risk, the use of macro signals has resurged as an active area of research.

Table 7: Macro Level Variables
Data from St Louis Federal Reserve, CBOE, and S&P Capital IQ

Category	Factor
Macroeconomic	Purchasing Managers Index Core CPI Inflation Consumer Sentiment
Capital Market	VIX Volatility Index Yield Spread (10-Fed) Market Returns

Given the binary nature of many regimes, logistic regression is often an appropriate technique to model the likelihood of the subsequent period regime. The Value/Momentum regime from the previous section has been carried forward. We selected a typical collection of macroeconomic and capital market variables, Table 7.

While an exhaustive screening of macro factors should yield stronger results, we found using this set sufficiently illustrative of the technique. Whenever possible, we have used the real-time data from the Federal Reserve Bank of St. Louis's ArchivaL Federal Reserve Economic Data (ALFRED) database. Unfortunately, point-in-time data is occasionally not available through our entire time period. In these instances, we appropriately lagged the time series. We also use Chicago Board of Options Exchange Volatility Index (VIX) data.

We formally define our problem as being predictive of a binomial response variable indicating forward relative performance of our two competing factors, 1 for EP and 0 for 12M1M. We estimate our initial model in-sample from 1991 to 1995. The regression used a number of different views of these high level factors (level, change, direction), and we fit our final model using a Stepwise AIC process. We find a combination of market performance, VIX, and consumer sentiment indicators provides the best fit in-sample. The model has some flexibility by estimating on an expanding basis, but we find these factors to be well represented throughout our test period. We tested the regression in-sample, out-of-sample, and with an expanding window re-estimating every period.

The output of logistic regression is interpreted as a log odds ratio. A more natural result can be found by taking the exponential of the output. This yields the estimated odds of observing a 1 in the following period (value outperformance in our example). The model performs strongly in-sample and weakly out-of-sample regardless of window. The hit rates for correct predictions are shown in Table 8. We attribute some of the weak performance to our regime selection. In reality, even though it can be distilled into a binary signal, there is an extremely wide range of realized relative performance. We observe differences ranging from 2bps to 45% in our test period.

Table 8: Macro Regression Hit Rates
Russell 3000, In-sample 1/31/1991 to 12/31/1995, Out of Sample/Expanding 1/31/1996 to 6/30/2011

	In Sample	Out of Sample	Expanding Window
Hit Rate	73%	48%	48%

We continue with this dynamic weighting exercise even with the weak model performance. As in the factor momentum section, we utilize two weighting schemes, fixed and informed, that incorporate the signal for relative factor performance. The same fixed tilt scheme (80%/20%) is used here. We take the exponential of our logistic output to convert it into a simple odds ratio. A value greater than (less than) 1 implies better odds that value (momentum) will outperform in the coming month. Our informed tilt uses our constructed odds ratio to determine the assigned factor weights. We should apply tilts that are related to our forecast conviction.

$$Fixed\ Tilt = .8(Factor_{out}) + .2(Factor_{under})$$

$$Odds\ Ratio = e^{logistic\ \ output}$$

$$Informed\ Tilt = Odds\ Ratio(EP) + \frac{1}{Odds\ Ratio}(PMOM)$$

We backtest these two dynamic strategies and compare to our equal weight benchmark in the Russell 3000 from January 1991 to June 2011. The results from these backtests are outlined below, Table 9. Not surprisingly, the performance of these models is less than spectacular.

Table 9: Macro Regression Monthly Performance
Russell 3000, 1/31/1991 to 6/30/2011

	Equal Weight	Fixed Tilt	Informed Tilt
Avg 1 Month Top Bottom	1.08%	0.90%	0.88%
Annualized IR	.44	.43	.43
Avg 1 Month IC	.052	.044	.046

MARKOV REGIME SWITCHING

Taking a purely statistical approach, we use a Hidden Markov chain Model (HMM) to capture the regime shifting characteristics of a time series (Hamilton 1989). This method assumes the time series switches between regimes following the first order Markov chain with unknown transition probabilities, Table 10.

Table 10: Example Transition Probability Matrix
P1=probability of Regime 1 given Regime 1, P2=probability of Regime 2 given Regime 2

	Regime 1	Regime 2
Regime 1	P1	1 – P1
Regime 2	1-P2	P2

These transition probabilities represent the likelihood of switching between two regimes in the HMM. If the current regime is Regime 1 (Regime 2), we will stay in Regime 1 (Regime 2) with probability P1 (P2), or we will switch to Regime 2 (Regime 1) with probability 1-P1 (1-P2). These regimes are not explicitly observed, so the chain is "Hidden". The observed data is assumed to have different distributions depending on the regime. For this paper, we assume that the observed data follows Gaussian distributions with different means and standard deviations in the two regimes. By maximizing the joint likelihood, we can estimate unknown parameters or find the probability of either regime at every period.

We applied the HMM method on the entire history of our Value and Momentum spread of spreads. The red line in Figure 4 shows the estimated probability of being in Regime 1 using the entire history's data for all estimates (Full History). The two periods with high probability of Regime 1 correspond with the most volatile periods in the spread of spreads, shown in Table 11. The regimes seem fairly stable in that the probability of moving to the opposing regime is fairly low in a given period. Table 12 outlines the transition probabilities for this process.

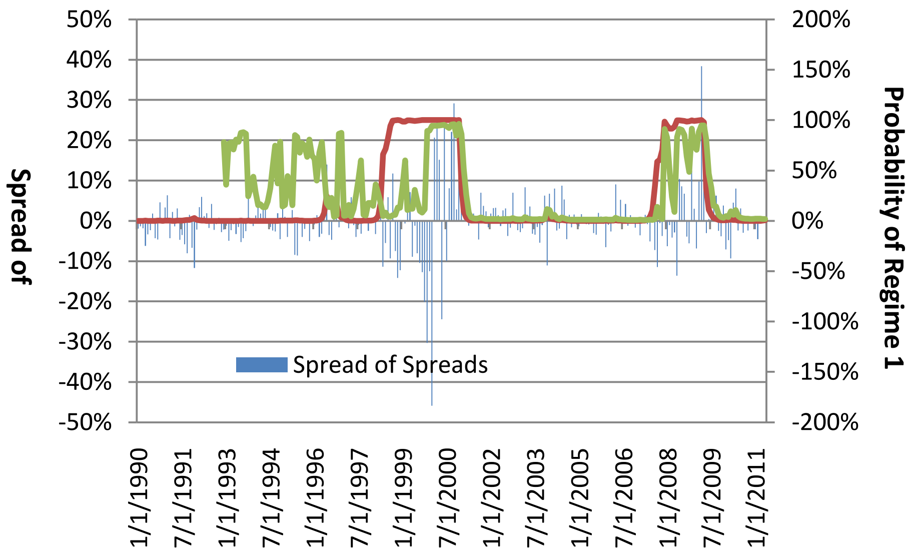
Table 11: Distribution of Spread of Spreads in Different Regimes
Russell 3000, 1/31/1990 to 6/30/2011

	Regime 1	Regime 2
Mean	0.62%	-0.23%
Standard Deviation	15.27%	4.01%

Table 12: Estimated Transition Probability Matrix of Spread of Spread Regimes
Russell 3000, 1/31/1990 to 6/30/2011

	Regime 1	Regime 2
Regime 1	0.951	0.049
Regime 2	0.013	0.987

Figure 4: Estimated Regime Probability given by HMM for Spread of Spreads
Russell 3000, 1/30/1990 to 6/30/2011, Red=Full History, Green=Expanding Window



We also applied the HMM methodology on an expanding window basis. Given the data is only available up to the given period (Expanding Window), we estimate the probability of being in each regime for the next period. The green line in Figure 4 shows the predicted probabilities for regime 1 using this expanding window. It effectively captures the majority the two volatile periods identified using the entire history. However, it failed to identify the regime before June of 1999. This is due to lack of high volatility regimes prior to that date.

Given the models ability to effectively identify these spread of spread volatility regimes, we investigate whether our regime prediction could improve our dynamic weighting strategies. In both regimes as identified by expanding window HMM, we obtain optimal weights for our two factor model by maximizing the IR of factor ICs (discussed further in following section). We then combine these two models based on the predicted probabilities of being in Regime 1 or 2.

$$Combined\ Model = probRegime1(Regime1\ Model) + probRegime2(Regime2\ Model)$$

We performed similar analysis for the VIX throughout our time period. We tested both of our models, incorporating spread of spread and VIX regimes, against an equal weight benchmark, Table 13. Both models outperform the equal weight benchmark with more significant ICs and wider spreads, but the differences are not significant at the 90% level.

Table 13: HMM Monthly Performance
Russell 3000

	05/1995 – 04/2011			05/2001-05/2011		
	Avg. IC	**IC T-Stat**	**Avg. Spread**	**Avg. IC**	**IC T-Stat**	**Avg. Spread**
Spread of Spreads	.071	4.90	2.18%	.039	2.99	0.31%
VIX	.063	5.11	1.92%	.036	2.80	0.27%
Equal Weight	.068	4.47	1.84%	.036	2.79	0.23%

CONTEXTUAL MODELING

To this point, we have highlighted dynamic modeling as a function of time and perceived market context. These methods apply the same factor weights across the universe. In this section, we focus on incorporating stock level context when assigning factor weights (Sorensen, Hua, and Qian 2005). This technique acknowledges that certain classes of stocks (e.g. high and low growth stocks) should be modeled differently. Contexts should reflect how investors naturally think about stocks, and our factors should behave differently across risk partitions.

The modeling procedure starts with the selection of appropriate risk contexts and alpha factors. We use 3 Year Beta (Beta), Size, Long Term Growth (LTG) and Book to Price (BP) as the risk contexts for our universe. Instead of EP and 12M1M as used previously, we use four themes from the Capital IQ US Growth Model (Value, Quality, Growth, and Price Momentum). We found the contextual results using a two factor model were unstable, and that a larger model yields more stable results.

The universe is partitioned into high and low subsets along the chosen context. We look to validate our context selection by comparing the ICs of our factors across these partitions. We are looking for significant differences in factor efficacy between our sub-universes. Our investment themes behave significantly differently in IC space across these contexts, Table 14. These results align with many known market phenomena. Our themes are generally more effective for small cap stocks. Momentum, Growth, and Quality are more important for stocks with high LTG.

Table 14: Average Monthly US Growth Theme ICs
Russell 3000, 1/31/1991 to 6/30/2011, t-stat for difference in means across high and low partitions

	NC	Beta		Size		BP		LTG	
	All	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Value	.041	.041	.047	.033	.062	.047	.046	.041	.037
t stat		(-1.29)		**(-5.73)**		(0.24)		(0.62)	
Quality	.034	.034	.033	.024	.048	.032	.043	.043	.022
t stat		(0.12)		**(-5.51)**		**(-2.55)**		**(4.27)**	
Growth	.031	.031	.031	.021	.046	.033	.036	.039	.020
t stat		(-0.01)		**(-6.13)**		(-0.63)		**(4.27)**	
Momentum	.040	.040	.017	.021	.049	.033	.040	.046	.014
t stat		**(2.24)**		**(-2.30)**		(-0.60)		**(2.81)**	

We move forward utilizing an IR of IC maximizing framework to ascertain optimal weights in the sub-universes. The weights are determined using the mean ICs and covariance matrix of ICs for our investment themes. If the correlations between the factors are zero, the optimal weight of a factor is proportional to the IR of its IC. We outline the monthly IR of ICs for our themes across all of our contexts and with "No Context" (NC), Table 15. No Context simply means we tested the factors for the entire universe agnostic of context.

Table 15: IR of Monthly US Growth Theme Factor ICs in Context
Russell 3000, 1/31/1990 to 6/30/2011

	NC	Beta		Size		BP		LTG	
	All	High	Low	High	Low	High	Low	High	Low
Value	0.93	0.71	0.90	0.57	1.02	0.87	0.84	0.60	0.68
Quality	0.82	0.64	0.71	0.48	0.94	0.63	0.81	0.68	0.46
Growth	0.82	0.64	0.73	0.50	0.86	0.68	0.77	0.66	0.44
Momentum	0.29	0.29	0.16	0.14	0.39	0.26	0.30	0.35	0.10

To obtain out-of-sample factor weights, we utilize an expanding window and update the factor weights every month.

With model weights determined for our sub-universes, we now must decide how to apply these weights to each security. We use a stock's "proximity" to the high and low partitions to weight the high and low models in a continuous fashion. The closer a stock is to the high-end of the risk partition, the more weight will be given to the high model. A composite model score is created by combining the ranks of the contextual model on an equal-weighted basis.

$$ptile = \%tile\ within\ risk\ partition$$
$$Stock\ Specific\ Model\ Weights = (ptile)(High\ Model) + (1 - ptile)(Low\ Model)$$

The model backtest results are very similar between the contextual and no context models (model weights determined using the IR maximization for entire universe), Table 16. Even though the contextual models generally lead in terms of raw Top-Bottom Spread and IC, they lag in terms of IR. Regardless of context, these optimal dynamic weighted models outperform the simple equal weight combination of our investment themes in IR space. The equal weight model leads in terms of monthly spread and IC, but these are not necessarily appropriate for comparison as the optimal weights were determined to maximize IR.

Table 16: Contextual Models Monthly Performance
Russell 3000, 1/31/1990 to 6/30/2011

	BP	LTG	Size	Beta	Composite	Equal	No context
Avg 1Mo T-B	1.78%	1.85%	1.83%	1.81%	1.84%	2.52%	1.77%
Annualized IR	.76	.80	.77	.81	.81	.50	.81
Avg 1 Mo IC	.052	.051	.050	.052	.051	.053	.049

These results piqued our interest. Why are the performance results so similar between contexts and in comparison to the no context optimization? Since the weight of a factor is strongly related to the IR of ICs, we reexamine the IR of ICs in Table 15. If we rank the themes by IR in all contexts and partitions, we see that our Value theme generally leads the group; the Quality and Growth themes float in the middle; and the Price Momentum theme lags behind. So, while the factors behave differently between high and low partitions, each investment theme has a similar strength relative to the other investment themes across the board.

Table 17: Average Factor Weights for All Models
Russell 3000, 1/30/1990 to 6/30/2011

	NC	Beta		Size		BP		LTG	
	All	High	Low	High	Low	High	Low	High	Low
Value	57.3%	56.8%	53.1%	51.8%	55.3%	61.5%	52.6%	49.2%	54.5%
Quality	37.4%	19.8%	20.0%	26.3%	31.2%	24.7%	29.8%	23.0%	29.4%
Growth	2.9%	19.3%	23.2%	17.5%	12.8%	12.7%	7.2%	21.5%	12.8%
Momentum	2.4%	4.0%	3.6%	4.3%	0.7%	1.1%	10.4%	6.3%	3.3%

We show the average factor weights for all contexts using the entire history, Table 17. We find that the weights of the factors are not dramatically different across high and low contexts, heavy value and light momentum. Consistent with prior research, our value theme has higher weights in High BP and Low LTG contexts, and our momentum theme mirrors value with higher weights in Low BP and High LTG contexts. The momentum factor has low weights due to its low mean and (more significantly) high variance of IC. Additionally, the continuous combination of the models has the effect of further diluting the score differences across the contexts. The average correlations between no-context and contextual model scores are as high as 97%.

We tested further variations of this model to see if they provided more differentiated results. We tried using different universes (Russell 1000 vs. Russell 3000) and window types (rolling vs. expanding). We also experimented with different measures of proximity such as binary (high/low) and schemes that shifted greater weight to the tails of the distribution. These tests all provided similar results. The contextual models did not generate additional benefit compared to the No Context optimization, but all the models with dynamic optimized weights outperform the equal weight model in IR space.

3 Summary

Modeling changing market dynamics proves to be challenging for the quantitative investor. We present a number of different approaches to this problem. Dynamic strategies incorporating macro and micro context *may* provide additional value, Table 18 and Table 19. However, we do not find the results to be significantly different than simple equal weight models for the contexts we tested (equal weight is hard to beat).

Given the variable factor efficacy identified using the Alphaworks Regime Monitor, incorporating regimes seems to be a natural extension and potentially fruitful path for equity managers. And, while our strategies didn't yield significantly different results from their appropriate benchmarks, we believe that the techniques outlined in this paper could add significant value in the right investment process.

Table 18: Performance Comparison of Dynamic Two Factor Models
Russell 3000, 05/31/1995 to 05/31/2011

	Avg. 1 Mo Spread	Ann. IR	Avg. 1Mo IC	Turnover
Equal Weight Model	1.11%	.41	.050	32.6%
Factor Momentum (Reg.Norm)	1.42%	.62	.049	44.6%
Factor Spread	1.17%	.49	.050	30.8%
Macro Regression	0.75%	.33	.038	43.8%
HMM (Spread of Spreads)	1.00%	.43	.052	35.1%

Table 19: Performance Comparison of Contextual Model using US Growth Themes
Russell 3000, 05/31/1995 to 05/31/2011

	Avg. 1Mo Spread	Ann. IR	Avg. 1Mo IC	Turnover
Equal Weight Model	2.53%	0.91	.052	43.5%
No Context	1.72%	1.29	.046	42.7%
Contextual Composite	1.80%	1.26	.048	42.9%

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OUR RECENT RESEARCH

July 2011: Introducing Research Briefs

Investors must sort through a constant stream of information in order to identify opportunities, structural changes, and market risks. Wading through information quickly and efficiently is critical as investors must understand how their strategy and exposures are impacted. Typical classes of questions include: What strategy should I use in response to a regime shift? How do I invest in a specific industry? Do other markets behave differently than the US market?

June 2011: Our Retail Industry Strategy

Does Industry Specific Data tell a Different Story? Investors are on a constant quest for new investment insights. A more complete understanding of the dynamics that shape an industry is integral to this search. As Capital IQ's Quantitative Research begins a more thorough examination of industry specific sources of alpha, we turn our attention first to the retail industry utilizing the Compustat database. Many of the strategies validate common investor best practice when looking at the retail space. In this paper we develop several new retail specific factors and use them to construct a 6-factor retail specific model. We then blend our retail model with our Value and Growth Composite Models.

May 2011: Introducing Capital IQ's Global Fundamental Equity Risk Models

Global investors invest in assets across multiple countries. In order to characterize the overall risk they need the ability to compute the total risk of their entire holdings. Using a global risk model summarizes the risk across multiple geographies into a more easily consumed single number rather than looking at the risk characteristics in isolation for separate geographies. A single global model also captures inter-country correlations so as to not miss important contagion effects.

May 2011: Topical Papers That Caught Our Interest

Favorite Papers on a Few Favorite Topics – Regime Switching and Minimum Variance
Two current topics of significant interest and frequent discussion to investors are regime switching, or a strategy's sensitivity to the current environment, and minimum variance portfolios.

April 2011 – Can Dividend Policy Changes Yield Alpha?

Investors are acutely sensitive to changes in dividend policy. Literature suggests that dividend change announcements provide information about management's assessment of companies' prospects, and therefore are predictive of future stock returns. The implication for investors is worth noting. In the first quarter of 2011 alone, 105 of the 384 dividend paying S&P 500 companies (27.3%) increased their dividends, while only 1 (0.26%) decreased dividends.
In this paper, we analyze the market reaction to different types of dividend policy changes, specifically initiation, increase, decrease and suspension of dividends.

April 2011: CQA Spring 2011 Conference Notes

Several of our team's members attended the Chicago Quantitative Alliance (CQA) Spring Seminar in Las Vegas. We present our collective notes from the conference in this report.

March 2011: How Much Alpha is in Preliminary Data?

Companies often report financials twice: first, through a preliminary press release and again in their official, i.e., final, SEC filings. In theory, there should be no difference between the numbers reported in a company's preliminary financial filings and their final filings with the SEC. In practice, often significant difference can occur between the preliminary and final filings. In this month's research report, we focus on these observed differences within the Capital IQ Point-In-Time database in order to ascertain the nature and exploitability of these differences.

February 2011: Industry Insights – Biotechnology: FDA Approval Catalyst Strategy

Biotechnology is a challenging sector for investors due to the binary nature of the product cycle. Indeed many biotechnology firms' futures rest upon the success of a single product. A critical stage in the product life-cycle is the FDA approval process. In this report we look at the exploitability of a strategy centered on FDA filings.

January 2011: US Stock Selection Models Introduction
In this report, we launch our four US Stock Selection models -- Value, Growth, Quality, and Price Momentum. Built using Capital IQ's robust data and analytics, these four models are the culmination of over two years of research and development. Each model is intended to be employed as the basis for a stand-alone stock selection strategy or integrated into an existing systematic process as an overlay or new component.

January 2011: Variations on Minimum Variance
Various explanations for why risk is mispriced have been offered; the most common one is that leverage restrictions incite some investors to chase volatility at the individual issue level. In this paper, we explore various methodologies for construction of minimum variance portfolios of US listed equities and analyze the features of these portfolios.

January 2011: Interesting and Influential Papers We Read in 2010
As researchers, we spend a large amount of time trying to generate new ideas. In order to discover and refine these ideas, we find ourselves in a continuous quest for innovative and interesting articles and papers from academics, analysts, and other researchers. There is such a large body of information out there that it can be difficult to wade through all the material to find what is truly of value and interest to us. To assist in sifting through all this information, our group recently took the time to find and discuss articles that recently struck us.

November 2010: Is your Bank Under Stress? Introducing our Dynamic Bank Model
Leveraging Capital IQ's Bank industry data, we have built a stock selection model that encompasses three themes -- Momentum, Value, and Balance Sheet Quality -- and includes a proprietary Markov-regime switching component which dynamically changes the model's weights depending on whether or not banks are in a “stressful” (or crisis) environment. This month, we will review how we built our model and its switching component.

October 2010: Getting the Most from Point-in-Time Data
In this paper, we will examine PIT data's origins, structure, variations, and proper use in implementations from Compustat and Capital IQ. Misusing PIT data, or applying it haphazardly, can discard valuable information and obscure otherwise clear signals.

October 2010: Another Brick in the Wall: The Historic Failure of Price Momentum
In 2009, investors witnessed the cataclysmic failure of Price Momentum strategies. Now that accounts of this failure have been on the books for some time, it is appropriate to place the events in a historical context and further analyze the fundamental relationships that affect this strategy. We look at a number of questions from practitioners interested in the strategy. Within a historical context, how pronounced has this recent failure been? When Price Momentum fails, what is the strategy's subsequent performance? And, what factors are concurrent or predictive of the performance of Price Momentum?

July 2010: Introducing Capital IQ's Fundamental US Equity Risk Model
In this paper we document the process of building and testing of our fundamental US Equity risk model across a number of short to medium term forecast horizons. The paper reviews typical risk model applications; discusses the relative merits of alternative forms of multifactor risk models; documents our data and methodology; 4 describes the chosen test metrics; and presents our results.