Hedging Sentiment Signals with MSCI Barra Risk Models

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November 2017

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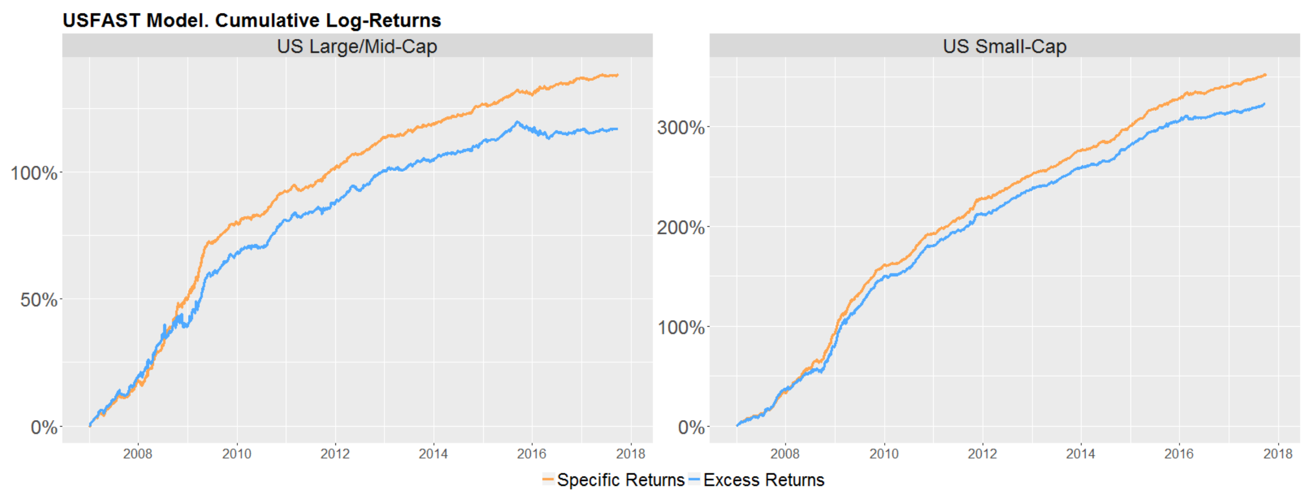
Executive Summary

In this study, we show how RavenPack's *Event Sentiment Score* can be predictive of stock returns after hedging the exposure to common risk factors. In particular, we move beyond excess returns to consider *specific returns* as defined by several distinct MSCI Barra risk models. The study showcases the significant benefits of using MSCI specific returns for building predictive models as we get cleaner, less volatile return profiles, meaning a marked improvement in risk-adjusted returns. Specifically, we find that:

- RavenPack Analytics adds consistent value in a daily strategy across both the U.S. and Europe – after accounting for MSCI risk factors.
- For the U.S., Information Ratios of 3.8 and 6.1 are achieved for the Russell 1000 and Russell 2000, respectively. Whereas, we get IRs of 3.2 and 4.2 for their Russell Europe equivalents (i.e. Large/Mid-Cap & Small-Cap).
- Sentiment factors tested within MSCI's regional risk models (Barra US Total Market Equity Trading Model - USFAST & Barra Europe Equity Derived-UK Model - EUE4DUK) outperform the global model (Barra Global Equity Model - GEM3) in terms of Information Ratio by 43% and 11% across large and midcaps; and by 19% and 3% on Small-Caps, respectively.
- The performance of the prediction quantiles shows the desired monotonic behavior - with more extreme predictions leading to more extreme returns.
- The predictive power of RavenPack's sentiment signals is both statistically significant and positive across the entire backtesting period.



Cumulative Log-Abnormal-Return Profiles. Performance of a daily long/short strategy based on RavenPack Analytics under MSCI specific returns (Barra US Total Market Equity Trading Model - USFAST) – for both Russell 1000 and 2000.

About RavenPack Data

RavenPack Analytics provides real-time structured sentiment, relevance and novelty data for entities and events detected in unstructured text published by reputable sources. Publishers include Dow Jones Newswires, Barron's, the Wall Street Journal, and over 19,000 other traditional and social media sites. 17 years of Dow Jones newswires archive and 10 years of historical data from web publications and blogs are available for backtesting. RavenPack detects news and produces analytics data on over 43,000 listed stocks, top products and services, all major currencies and commodities, financially relevant places and organizations, and key business and political figures.

1. Introduction

When evaluating the efficacy of a trading signal, for simplicity researchers often use *excess returns*. This is equivalent to assuming just a single risk factor (the market) with constant factor exposure ($\beta = 1$) – inspired by CAPM [1]. However, in reality, several other risk factors exist and exposure not only differs across time, but also across assets. This can lead to erroneous conclusions when it comes to signal performance, both in terms of signal return and volatility. To truly isolate the effects of a given signal, we need to account for the contributions from a broader set of risk factors and ensure that any observed performance cannot be explained by known risk premia [2, 3, 4, 5].

The use of news sentiment has recently been a broadly treated research subject [6, 7]. In particular, in our previous paper [8], we introduced a simple daily strategy based on average sentiment per company. We showed how companies with positive return predictions outperformed companies with negative return predictions across various investment horizons. In this paper, we aim to build upon this previous study by introducing a risk model to examine the performance of RavenPack sentiment signals after taking into account the contributions from the market, industries, and styles such as value, momentum, size and many others.

In particular, we move beyond excess returns to consider the *specific returns* as defined by several distinct MSCI risk models. This is done as a convenient shortcut to a factor-neutral portfolio implementation. In this context, we evaluate the effect of applying a regional model vs. a global model (USFAST/ USMED vs. GEM3 in the U.S. and EUE4DUK vs. GEM3 in Europe), and faster vs. slower factors (USFAST vs. USMED within the U.S.). Furthermore, it allows us to isolate the alpha generated by our sentiment signal.

As part of this research, we will focus on three different topics: (1) we will perform an analysis on the different signal implementations using the specific returns from the different risk models; (2) we will showcase the benefits of constructing signals based on specific returns including an analysis on the quantile performance; and (3) we will perform an evaluation of the signal speed or decay. As our findings are consistent and robust across both U.S. and Europe, we will focus primarily on the U.S. region, providing a summary of the European results in Appendix A.

The layout of this paper is as follows. Section 2 provides an overall description of the data used in this research. We explain how to build the reference indicator to predict specific returns provided by the risk models and outline the regression framework we implement in order to produce our trading signals. Results for the various risk-based signals are presented and discussed in Section 3. Finally, in Section 4, our general conclusions are provided.

2. Data & Model Description

To create our sentiment signals, we use RavenPack's *Event Sentiment Score (ESS)*, which is part of the RavenPack Analytics 1.0 analytical suite[1]. Since previous research has shown that highly relevant and novel events hold stronger return predictability [5], we condition our signal on RavenPack's *Event Relevance (ERS)* and *Event Similarity Days (ESD)* scores - setting both ≥ 90. In addition, we only consider non-neutral events ($ESS \neq 0$). For our backtest, we consider a 10-year period covering January 2007 through September 2017 for U.S. companies belonging to the Russell 1000 and Russell 2000 indices in a point-in-time sensitive fashion.

In contrast to previous papers [9, 10], where we measured strategy performance using excess returns, in this case we use specific returns[2] extracted from a variety of MSCI risk models. Although strategies based on specific returns are not directly tradeable unless we use factor mimicking portfolios, we aim to show how RavenPack Analytics still adds value even after accounting for the contributions of the factors included in commercial risk models. In particular, we will consider the following daily risk models offered by MSCI[3]:

- **GEM3:** The Barra Global Equity Model (GEM3) incorporates the latest advances in risk methodology to help fund managers construct, manage, and analyze global equity portfolios. The model offers a refined style factor lineup that includes: 11 style factors, 34 industry factors, 77 country factors, 77 currency factors, and one world factor.
- **USMED:** The Barra US Total Market Equity Model for Medium-Term Investors (USMED) is designed to understand and predict sources of performance and risk for U.S. investors. In particular, USMED is built to capture risk in the medium term, suitable for investment horizons between one month and one year. The model comprises 21 style factors, 60 industry factors, and one country factor.
- **USFAST:** The Barra US Total Market Equity Trading Model (USFAST) has very similar features to USMED as it is also focused on the U.S., but oriented towards a shorter investment horizon – including, for instance, a short-term reversal factor. In terms of its composition, the model includes 24 style factors, 60 industry factors, and one country factor.

To evaluate the efficacy of the sentiment signal, similar to previous research [8, 9], we adopt the following simple linear regression model to predict returns[4], which are estimated using OLS:

[1] RavenPack Analytics (RPA) structures relevant information from more than 19,000 providers including Dow Jones Newswires, the Wall Street Journal, MarketWatch, Barron's, Benzinga, The Fly, MT Newswires, Alliance News, and FactSet, among many others. The data feed covers events over 192,000 entities which are assigned in real-time to one of nearly 7,000 categories across 56 groups in five topics. For additional information on RavenPack Analytics and the various scores, we refer to the "RavenPack Analytics User Guide".
[2] Also called abnormal returns in the literature.
[3] We refer the reader to the MSCI website (www.msci.com), where more detailed information about the models is available.
[4] The approach is valid both for excess and specific returns.

$$Return_{i,t+1} = \alpha + ESI_{i,t} \cdot \beta + e_{i,t+1} \quad (1)$$

where $e_{i,t+1}$ is a scalar disturbance term for asset i on day $t + 1$, and ESI (Entity Sentiment Indicator) is the sentiment signal[5], which is defined as:

$$ESI_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} ESS_{i,t,j} \quad (2)$$

So for a given asset i, the daily indicator is the average sentiment of events, $j \in \{1, \dots, N_{i,t}\}$, happening on day t that meet the relevance and novelty filters of ERS ≥ 90 and ESD ≥ 90. Regression coefficients, $\hat{\alpha}$ and $\hat{\beta}$, are re-estimated on a monthly basis[6], using one year's worth of data. Every day, we use the estimated coefficients to predict the one-day ahead returns ($\hat{\alpha} + ESI_{i,t} \cdot \hat{\beta}$) for all those companies with an ESI at time t. A day is defined as 24 hours starting from 30 minutes before market close (local time), which provides a 30 minutes window to rebalance the portfolio on a daily basis[7].

3. Results & Discussion

To evaluate our sentiment signal, we create a set of long-short portfolios using the three risk models and various aggregation windows. In particular, we go long stocks with positive specific-return predictions and short stocks with negative specific-return predictions. Portfolio weights are determined by the relative predictions and are normalized daily to ensure a total gross exposure of 1, subject to a maximum allocation constraint of 5% on each stock. The following subsections will rely on this to present three different areas of discussion: (1) signal comparison, (2) strategy performance, and (3) signal decay.

3.1 Signal Comparison

Using the above long-short portfolio framework, Figure 1 provides an Information Ratio (IR) comparison across the signals implemented upon the three risk models. In addition, to evaluate both faster and slower versions of the signal, we also consider a set of sentiment aggregation windows to get a sense of the performance impact. As can be observed, the performance of the sentiment signal is stronger when applying any of the two U.S. specific models[8] compared to the global model. In particular, we obtain an IR of 3.76 from the sentiment signal with a one-day aggregation window using the USFAST model and an IR of 2.63 using the GEM3 model - both on the Russell 1000 universe.

[5] Referred to as the *Event Sentiment Indicator (ESI)* in previous research [8, 9].
[6] There is no significant improvement when using daily re-estimation, as in [8]. Hence, for computational reasons, re-estimation of model parameters is done on a monthly basis.
[7] Returns are considered close-to-close
[8] USFAST and USMED.

Comparing the signals from the two U.S. models, i.e. USFAST and USMED, we find consistently stronger performance from the sentiment signal created upon the faster model, which is reasonable given that the USFAST model is designed for shorter investment horizons and incorporates three additional high turnover, price based factors including 1-day and 1-month reversal as well as seasonality. Thus, the fact that the specific returns from USFAST account for the contributions from high turnover technical factors, allows the sentiment signal to really zero in on the component of returns that is unique to sentiment. This may well drive the sentiment signal's stronger performance in the USFAST model.

In terms of signal decay the IR drops fairly rapidly for the Russell 1000 – going from 3.76 to 1.61 as we increase the aggregation window from one day to one week. However, the reduction in IR is much less for the Russell 2000 universe, which still produces an IR above 2.2 with an aggregation window of one month. We see the same pattern of IR decay using the USMED and GEM3 models. This is an improvement of 191% on the GEM3 model and of 22% on the USMED model for the same aggregation window. We will further analyze decay in terms of temporal evolution of the return profiles in Section 3.3.

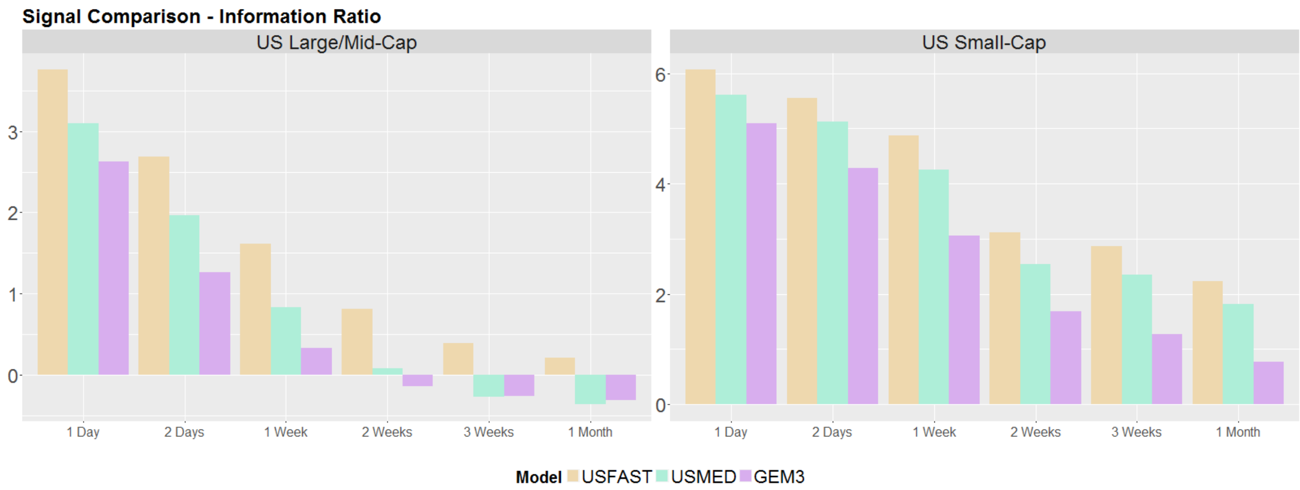


FIGURE 1: Information Ratio Comparison Across Signals. Performance is shown for both U.S. Large/Mid-Cap and Small-Cap across different signal aggregations, ranging from one day to one month.

Source: RavenPack, MSCI, October 2017

In Figure 2 we examine daily turnover rates for the sentiment signal across models and find essentially identical turnover rates across the three of them. As expected, we find that increasing our sentiment aggregation window leads to slower signals – with a one-month aggregation window being equivalent to a three-week holding period regardless of the universe. Hence, turnover rates seem to be driven by the underlying signal rather than by the choice of risk model.

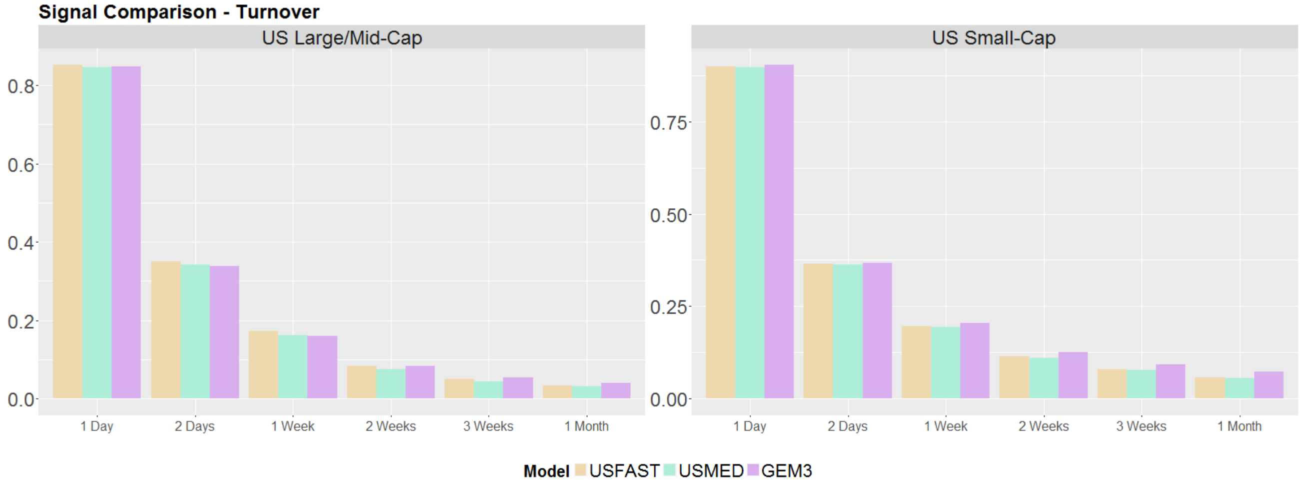


FIGURE 2: Turnover Comparison Across Signals. Daily (two-way) rates are shown for both U.S. Large/Mid-Cap and Small-Cap, for different aggregation periods, ranging from one day to one month.

Source: RavenPack, MSCI, October 2017

To get a better sense of what is driving the differences in IR of the sentiment signal across the risk models, we display both return and volatility in Figure 3.

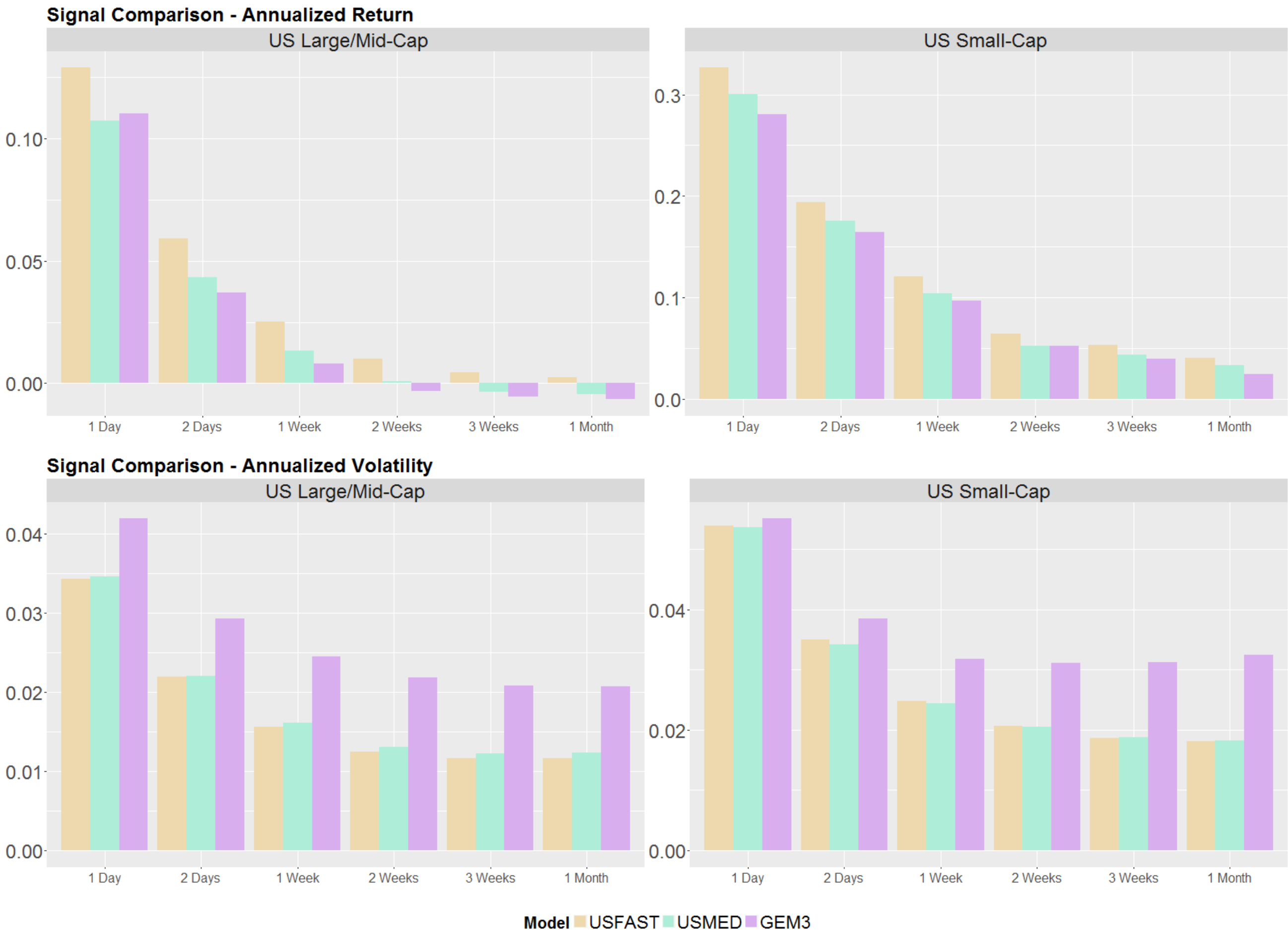


FIGURE 3: Comparison of Information Ratio Components Across Signals. Annualized Returns (top) and Annualized Volatility (bottom) is shown for both U.S. Large/Mid-Cap and Small-Cap across different signal aggregations, ranging from one day to one month.

Source: RavenPack, MSCI, October 2017

As can be observed, for Russell 1000, improvements in IR are driven both by higher returns and lower volatilities. However, for Russell 2000, the picture is slightly more complex. Comparing the USFAST and USMED models, the IR improvements are driven primarily by higher returns, while comparing to the GEM3 model, the IR improvements are driven by both higher returns and lower volatility. Overall, we find that applying the USFAST or USMED models lead to significant reductions in return volatility, and therefore “cleaner” sentiment signals.

3.2 Performance Comparison

Having compared the different signals created from MSCI models in the previous section, we now proceed to compare the performance of the USFAST specific returns against excess returns.[9] We have chosen to focus on the USFAST model because of its superior performance, but results for the USMED and GEM3 models can be found in Appendix B.

[9] Excess returns are measured relative to an equally-weighted portfolio across each universe.

Figure 4 shows the cumulative (log) return profiles of both the specific and excess return strategies. Performance is fairly stable over the 10-year backtesting period with a regime shift taking place after the Global Financial Crisis. Clearly, by accounting for the contributions of other factors (using specific returns), we not only outperform the excess return benchmark in total returns, but also in IR – which is achieved by a significant reduction in volatility (see Table 1). The importance of accounting for the contributions of other factors has been especially high over the last couple of years. In particular, with excess returns, the Russell 1000 portfolio's performance has flat-lined since 2016. However, this is not the case when evaluating against specific returns.

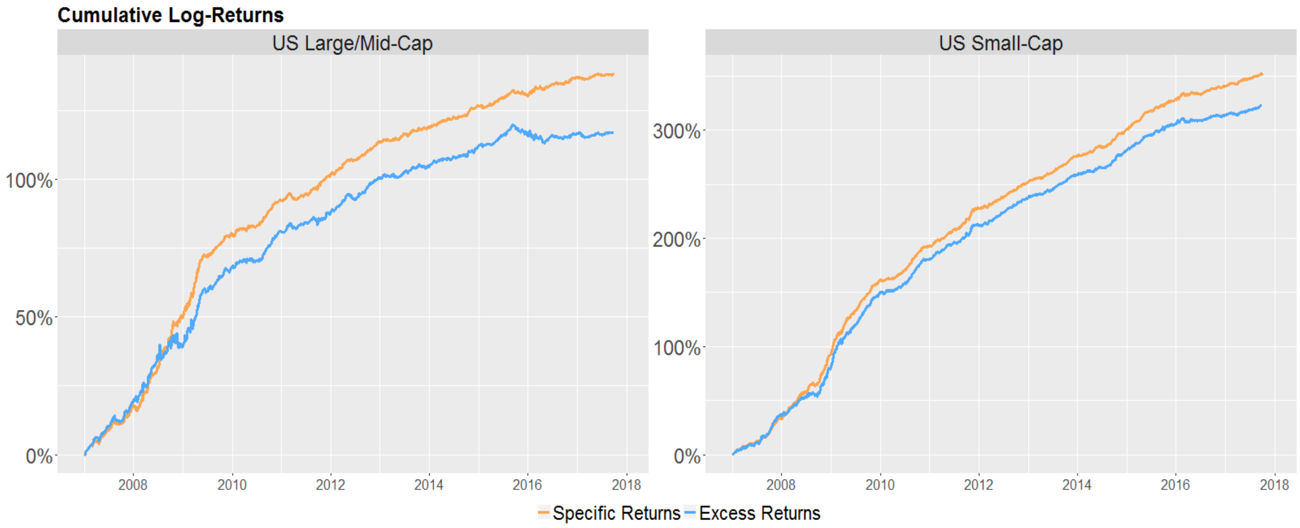


FIGURE 4: Cumulative Return Profile Comparison for USFAST Model. Comparison between MSCI specific returns and excess returns for a daily strategy on a one-day aggregated RPA signal. Results are shown U.S. Large/Mid-Cap (left) and Small-Cap (right) Universes.

Source: RavenPack, MSCI, October 2017

USFAST Model	Large/Mid-Cap		Small-Cap	
Statistics	**Specific Ret**	**Excess Ret**	**Specific Ret**	**Excess Ret**
Annualized Return	12.89%	10.89%	32.66%	30.13%
Annualized Vol.	3.43%	4.50%	5.38%	6.12%
Information Ratio	3.76	2.42	6.07	4.92
Avg. Portfolio Size	188	190	193	193
Max. Drawdown	2.31%	6.40%	2.81%	4.42%
Turnover	85.2%	83%	89.9%	89.5%

TABLE 1: Experimental Stats. Comparison between MSCI specific returns and excess returns for a set of statistics. Results are shown for USFAST model for Large/Mid-Cap and Small-Cap.

Source: RavenPack, MSCI, October 2017

Considering the predictive power of our signals, we find that they are not only statistically significant (as shown in Appendix C), but also show a monotonic behavior across quantiles. In Figure 5, we split the long-only strategy into five equally sized buckets, both for Large/Mid-Cap and Small-Cap, and evaluate the performance. We see that the more extreme predictions lead to more extreme returns. In addition, as volatility levels are almost identical across quantiles, the Information Ratio shows a similar increasing pattern, as depicted in Figure 6.

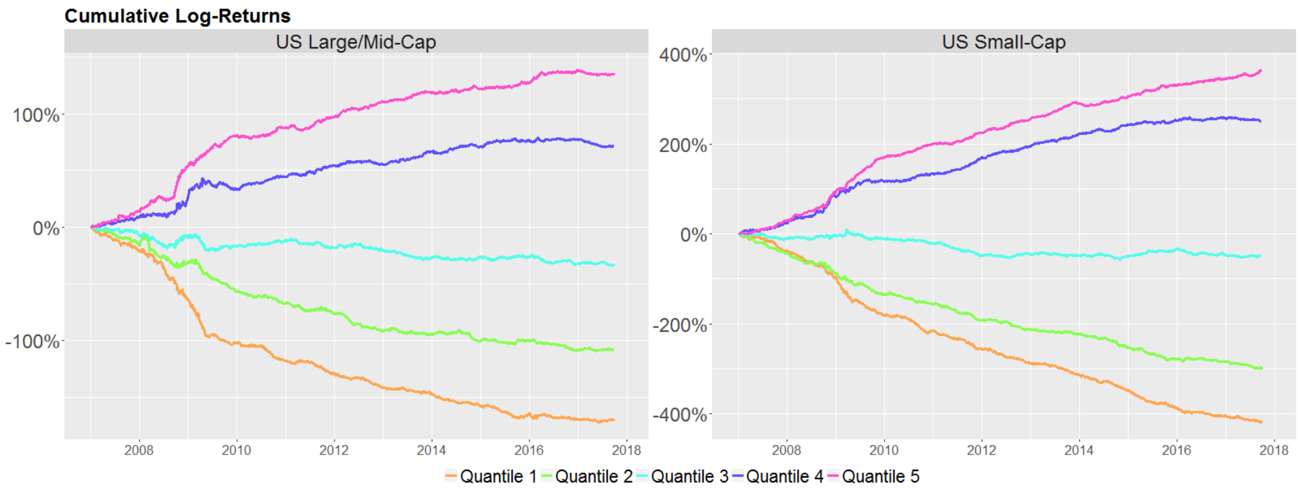


FIGURE 5: Quantile Comparison for USFAST Model Signal. Comparison among sentiment signal quantiles using MSCI specific returns in terms of cumulative log-returns profile. Results are shown for U.S. Large/Mid-Cap (left) and Small-Cap (right) universes.

Source: RavenPack, MSCI, October 2017

The results highlight the potential of significantly increasing strategy performance by only trading extreme quantiles – potentially more than doubling the annualized returns. However, this comes at a cost of smaller portfolios as we only trade 40% of the signal universe – something which may be less desirable for quantitative investors, but attractive for more discretionary users.

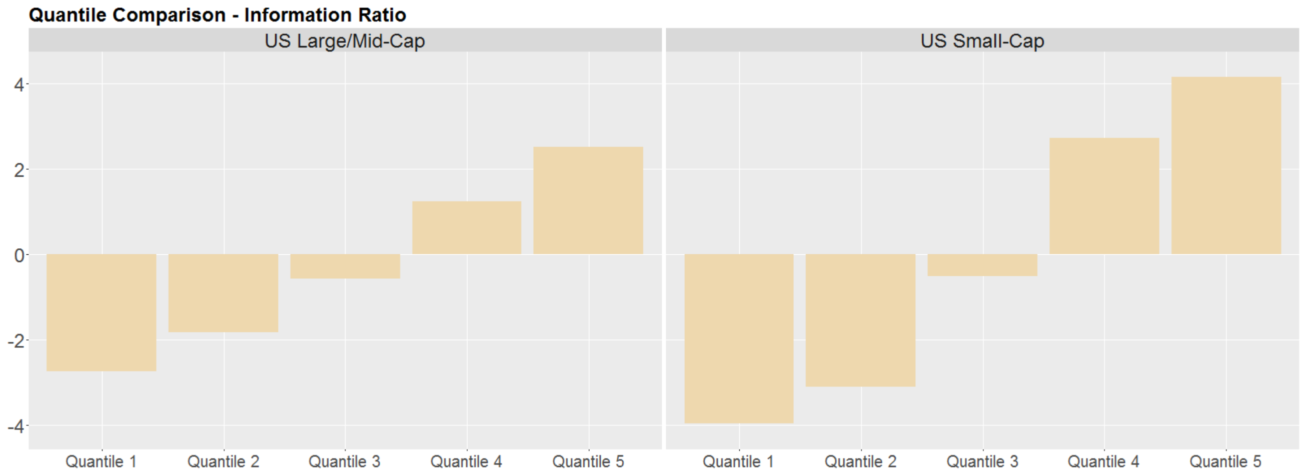


FIGURE 6: Quantile Comparison for USFAST Model Signal Comparison among prediction quantiles using MSCI specific returns in terms of information ratio. Results are shown for U.S. Large/Mid-Cap (Left) and Small-Cap (Right) Universes.

Source: RavenPack, MSCI, October 2017

3.3 Decay Analysis

To analyze signal decay, we stay at the daily trading frequency but smooth the daily predictor (ESI) before plugging it into the OLS regression framework. The benefits of this are two-fold: (1) we can continue to use our framework introduced above, and (2) comparisons with the results obtained in previous sections are straightforward. We use different aggregation windows, ranging from one day to one month.[10]

In terms of return profiles, and focusing on the USFAST model, Figure 7 shows a comparison across different signal aggregation windows for Russell 1000, i.e. 1-day, 2-days, 1-week, and 2-weeks. As can be observed, we see consistently better performance in returns and volatility using specific returns as compared to excess returns.

[10] As an alternative, we could have analyzed the predictive power of sentiment after *x* days by trying to predict the returns using *x*-day lagged sentiment. We refer the reader to Appendix D where a brief analysis on this idea can be found.

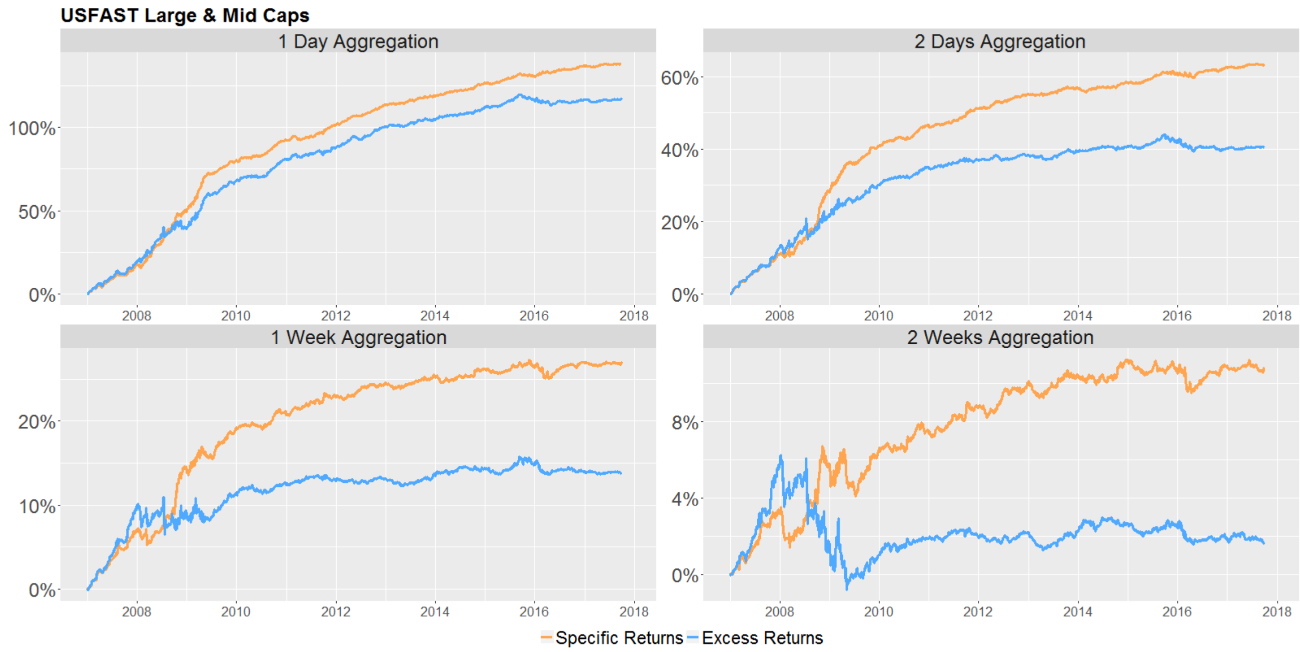


FIGURE 7: Cumulative Return Profile Comparison for Different Aggregation Periods. USFAST - Russell 1000. Results are shown for one day, two days, one week, and two weeks.

Source: RavenPack, MSCI, October 2017

Figure 8 shows a similar analysis for Russell 2000. However, in this case, we observe a much slower decay, providing steady performance even after the one-month signal aggregation. Similar to Russell 1000, again, the specific return signals not only provide higher cumulative returns, but also lower volatilities. This implies a significant improvement in Information Ratio regardless of the length of the aggregation window.

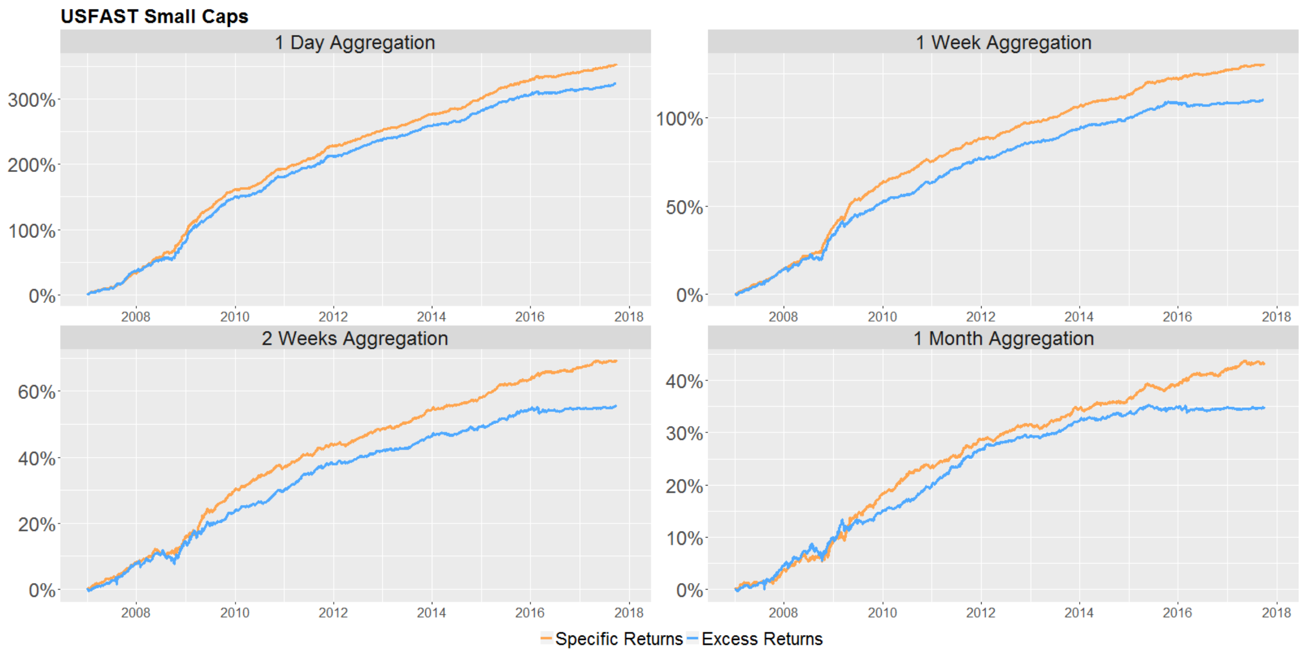


FIGURE 8: Return Profile Comparison for Different Aggregation Periods. USFAST - Russell 2000. Results are shown for one day, one week, two weeks, and one month.

Source: RavenPack, MSCI, October 2017

4. Conclusion

In this paper, we set out to evaluate the performance of RavenPack's event sentiment score after accounting for the return contributions from all other factors in MSCI risk models. In particular, we move beyond excess returns to consider *specific returns* as defined by several distinct MSCI risk models, including USFAST, USMED, and GEM3 to evaluate the effect of a country-specific vs. a global model, and faster vs. slower factors.

We answer this by first creating an average sentiment indicator from RavenPack Analytics (RPA) and use it as a predictor for one-day forward (specific) returns. Our results show that it is possible to extract alpha using RPA – even after accounting for common risk factors. In fact, there are strong benefits from using MSCI specific returns for building predictive models as we get cleaner, less volatile return profiles, meaning a marked improvement in risk-adjusted returns.

This conclusion holds across all evaluated risk models, but the best results are archived by applying the USFAST model as it better matches the underlying decay of the RavenPack news sentiment signal. In particular, we find that the signal decay is measured in days and weeks for Russell 1000 and 2000, respectively. Overall, by moving from excess to specific returns, we are able to improve the Information Ratio from 2.4 to 3.8 for the Russell 1000 universe and from 4.9 to 6.1 for the Russell 2000 universe – on a one-day aggregation period, whereas for one week, Russell 1000 improves from 0.6 to 1.6 and Russell 2000 from 3.7 to 4.9.

We also find that the predictive power of the signal is statistically significant and positive across the evaluated period. On top, the prediction quantile analysis shows a desirable profile, providing higher returns for more extreme predictions, something that could be exploited to increase return performance by only trading on extreme quantiles (at the cost of a smaller portfolio size).

Finally, an equivalent analysis across our European portfolios (Appendix A) provides very similar conclusions – highlighting the robustness of our results.

In future research we aim to explore other paths– and perhaps strengthen – the results presented in this paper. Among them, we would like to take advantage of RavenPack's taxonomy to study the impact of MSCI specific returns at the event-group level.

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Appendix A: European Models Result Summary

In order to evaluate the methodology performance in Europe, in addition to the GEM3 model described in Section 2, we make use of a region specific model, EUE4DUK. This model is oriented towards a short investment horizon and comprises two market factors, 11 style factors, 58 industry factors, 34 country factors and 35 currency factors.

In the following three subsections, we present the European results mimicking the ones provided on the Section 3 of the paper. From the results we draw very similar conclusions as the ones we got for U.S., showing the robustness of the proposal.

A.1 Signal Comparison

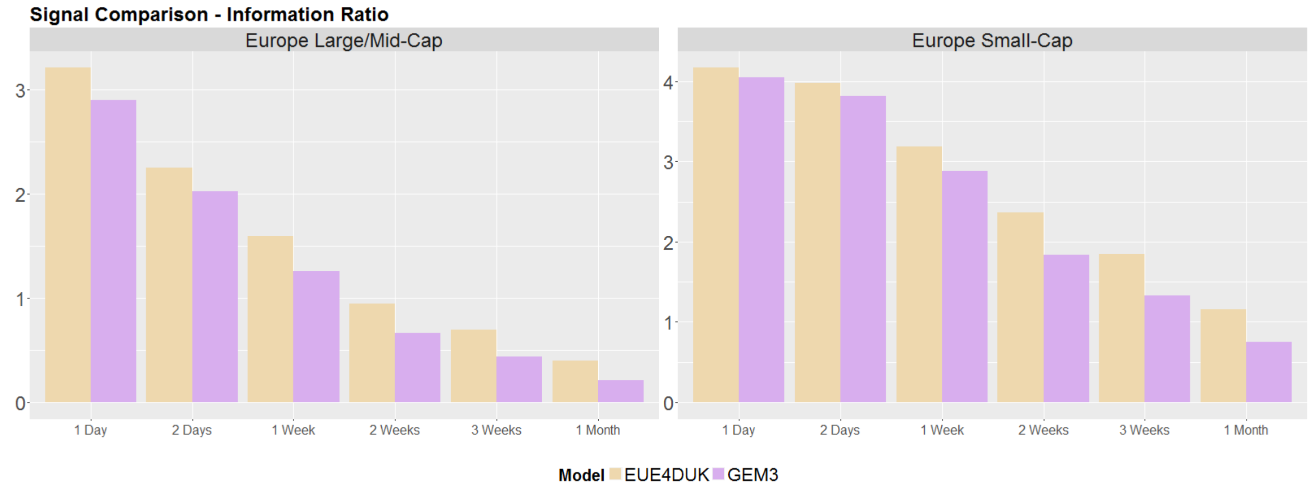

FIGURE A.1.1: Information Ratio Comparison for European Models Signals. Performance is shown for Large/Mid-Cap and Small-Cap across different signal aggregations, ranging from one day to one month.

Source: RavenPack, MSCI, October 2017

FIGURE A.1.2: Comparison of Information Ratio Components Across European Models Signals. Annualized Returns (top) and Annualized Volatility (bottom) is shown for both European Large/Mid-Caps and Small-Caps across different signal aggregations, ranging from one day to one month.

Source: RavenPack, MSCI, October 2017

A.2 Performance Comparison

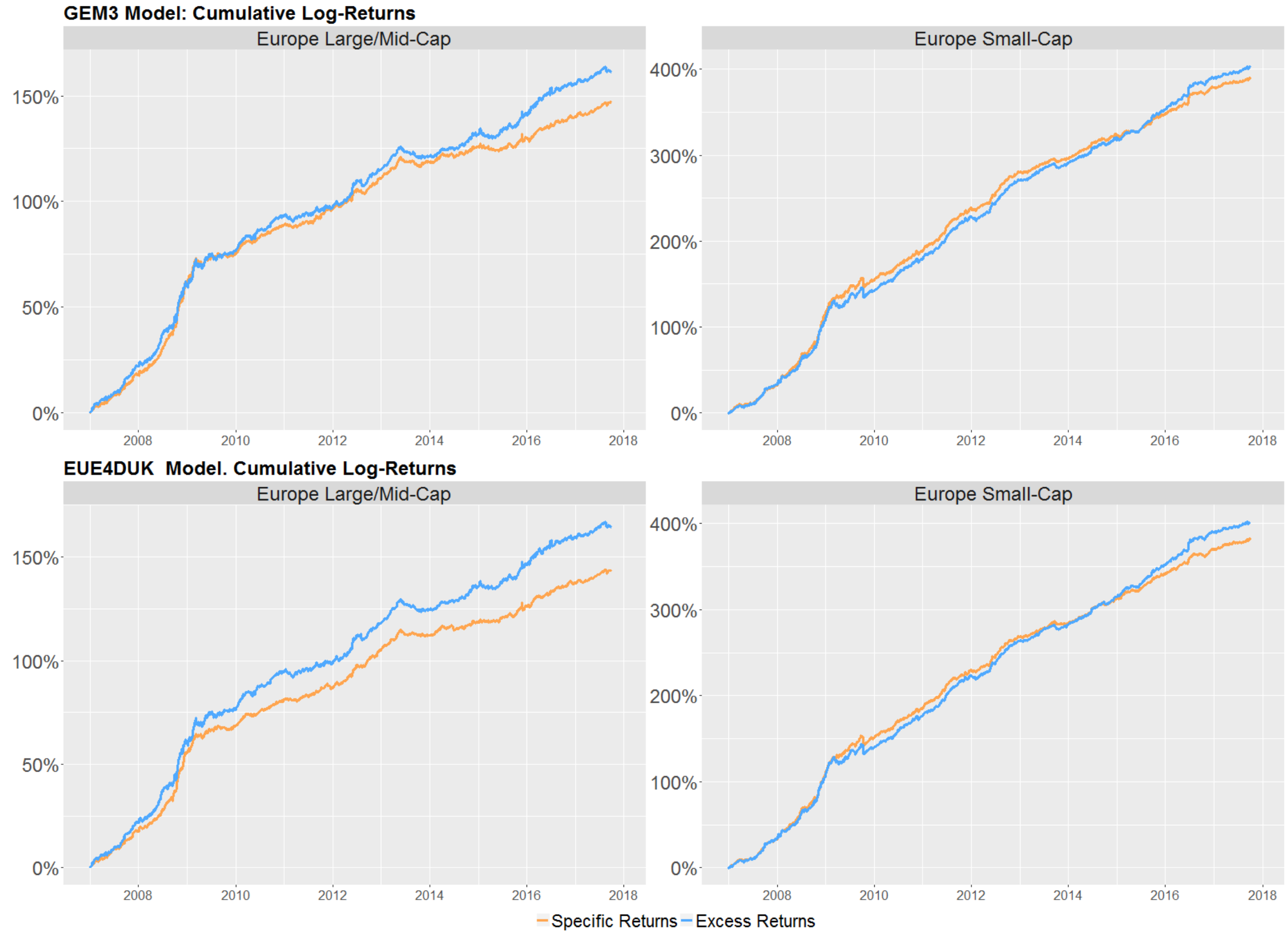

FIGURE A.2.1: Cumulative Return Profile Comparison Across MSCI Models Signals. Comparison between MSCI specific returns and excess returns for a daily strategy on a one-day aggregated RPA signal. Top: MSCI GEM3 model. Bottom: MSCI EUE4DUK Model. In both cases, results are shown for European Large/Mid-Cap (left) and Small-Cap (right) universes.

Source: RavenPack, MSCI, October 2017

	EUE4DUK Model				GEM3 Model			
	Large/Mid-Cap		Small-Cap		Large/Mid-Cap		Small-Cap	
Statistics	Specific Ret	Excess Ret	Specific Ret	Excess Ret	Specific Ret	Excess Ret	Specific Ret	Excess Ret
Annualized Return	12.90%	14.80%	34.46%	36.13%	13.20%	14.52%	35.10%	36.16%
Annualized Vol.	4.02%	5.68%	8.27%	9.05%	4.55%	5.62%	8.67%	9.14%
Information Ratio	3.21	2.60	4.17	3.99	2.90	2.58	4.05	3.96
Avg. Portfolio Size	96	97	47	47	98	99	48	48
Max. Drawdown	3.76%	5.92%	10.29%	11.23%	4.64%	5.64%	10.04%	11.31%
Turnover	85.8%	84.1%	91.8%	91.9%	85.6%	84%	91.7%	91.8%

TABLE A.2.1: Experimental Stats. Comparison between MSCI specific returns and excess returns for a set of statistics. Results are shown for EUE4DUK and GEM3 models both for Large/Mid-Cap and Small-Cap.

Source: RavenPack, MSCI, October 2017

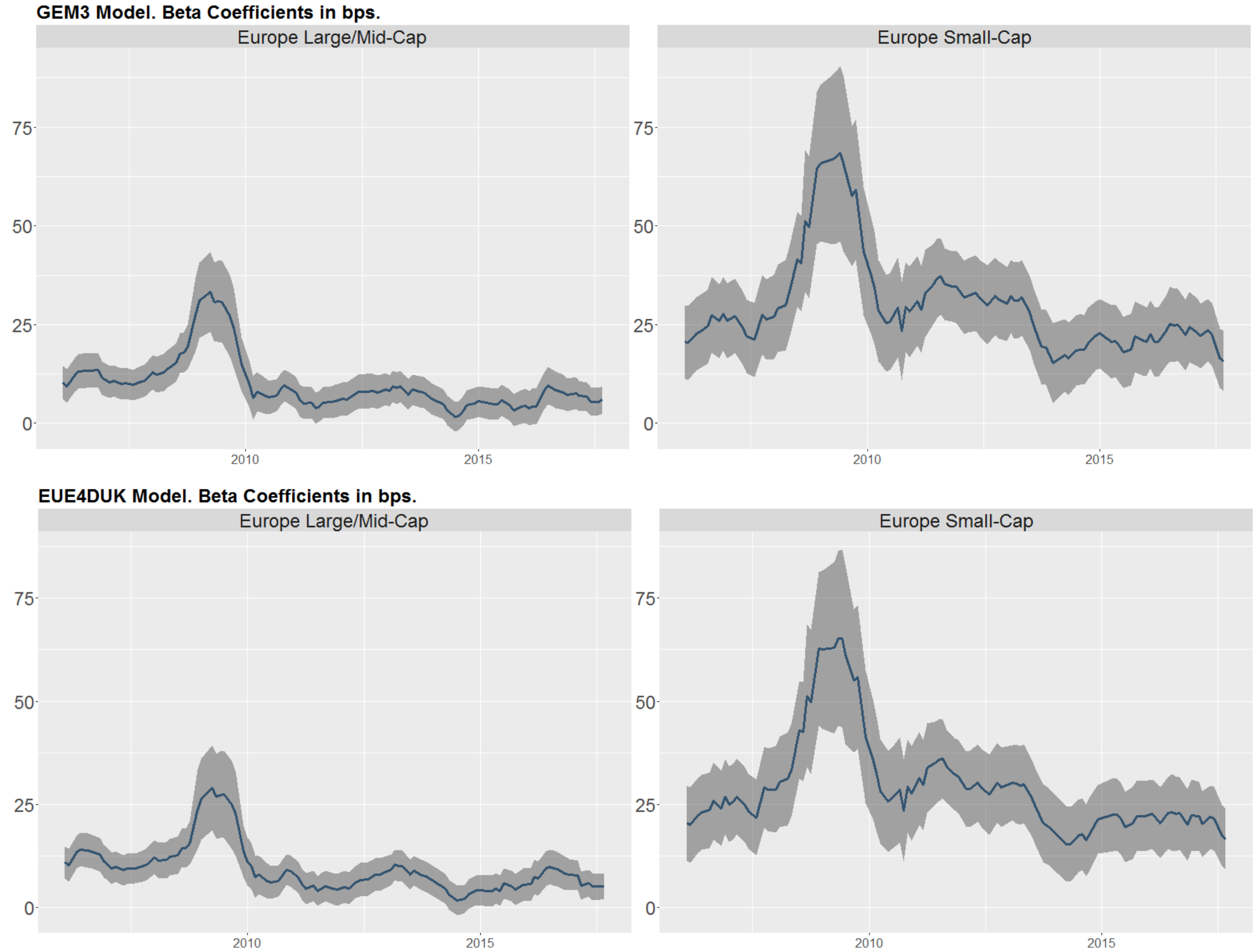

FIGURE A.2.2: Estimated ESI Coefficient by Market Capitalization Across MSCI Models. GEM3 (top), and EUE4DUK (bottom) results are shown for Large/Mid-Caps (left) and Small-Caps (right). Notice that the coefficients (y-axis) are multiplied by 10,000 and can be interpreted as the number of basis points the ESI adds to the overall log-return prediction for a given level of ESI. We can see that for all experiments the coefficients remain significant across time, which confirms the strength of using ESI as a return predictor. Not surprisingly, due to market inefficiencies, the small-cap coefficients are "stronger" than the Large/Mid-Cap ones.

Source: RavenPack, MSCI, October 2017

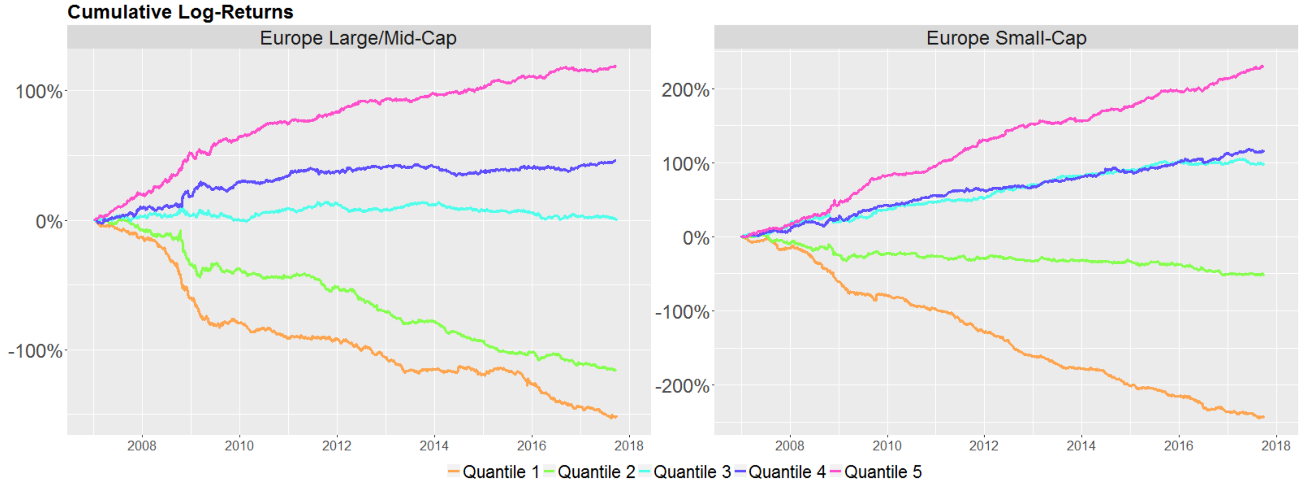

FIGURE A.2.3: Quantile Comparison for EUE4DUK Model Signal. Comparison among prediction quantiles using MSCI specific returns in terms of cumulative log-returns profile. Results are shown for European Large/Mid-Cap (left) and Small-Cap (right) universes.

Source: RavenPack, MSCI, October 2017

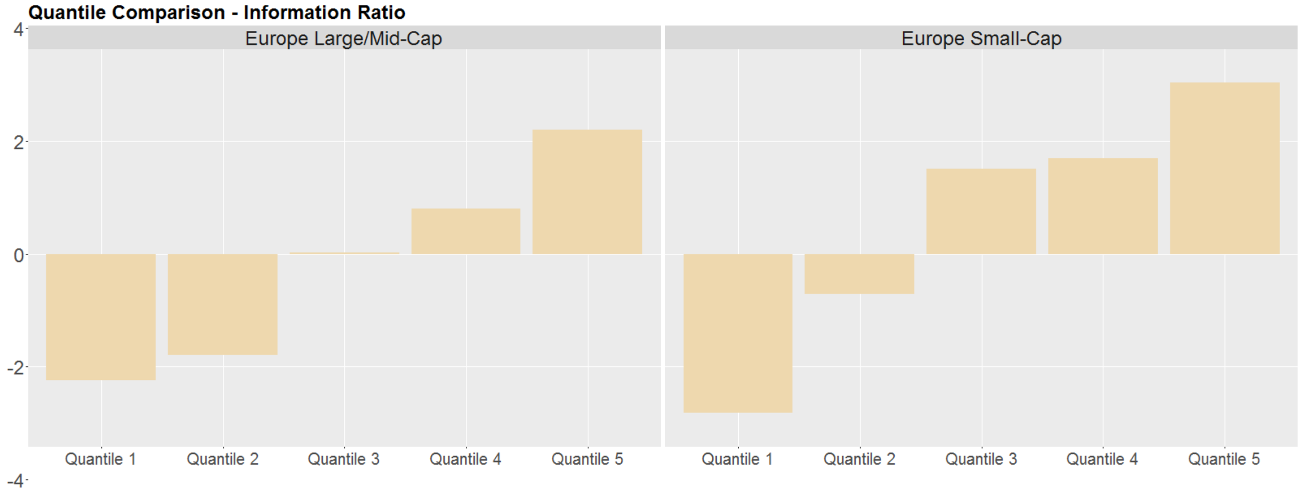

FIGURE A.2.4: Quantile Comparison for EUE4DUK Model Signal. Comparison among prediction quantiles using MSCI specific returns in terms of IR. Results are shown for European Large/Mid-Cap (Left) and Small-Cap (Right) Universes.

Source: RavenPack, MSCI, October 2017

A.3 Decay Analysis

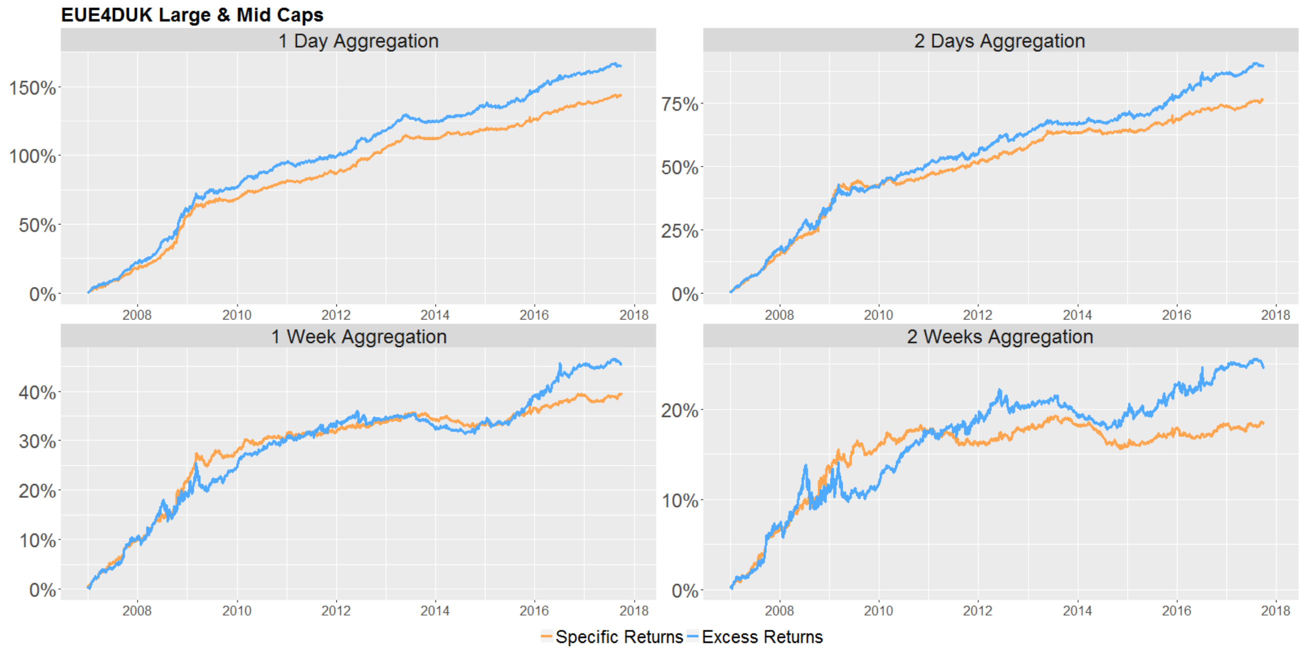

FIGURE A.3.1: Cumulative Return Profile Comparison for Different Aggregation Periods. EUE4DUK Large/Mid-Caps. Results are shown for one day, two days, one week, and two weeks.

Source: RavenPack, MSCI, October 2017

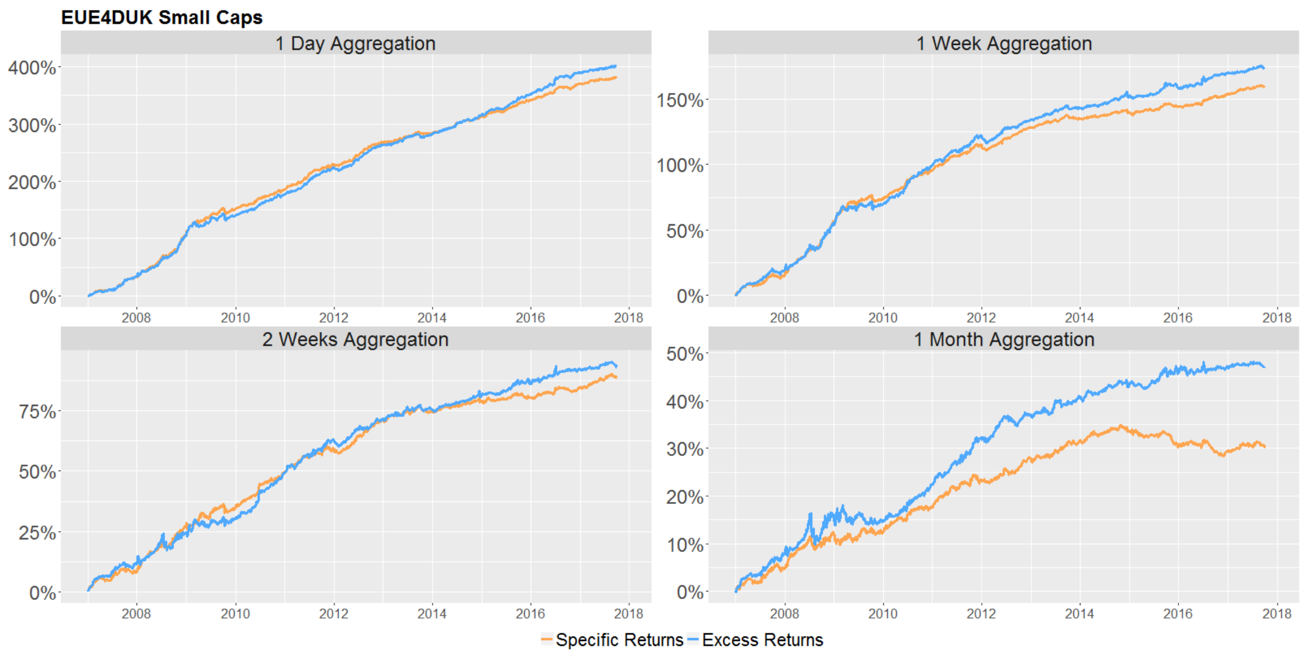

FIGURE A.3.2: Return Profile Comparison for Different Aggregation Periods. EUE4DUK – Small-Caps. Results are shown for one day, one week, two weeks, and one month.

Source: RavenPack, MSCI, October 2017

Appendix B: GEM3 and USMED Models Performance Results

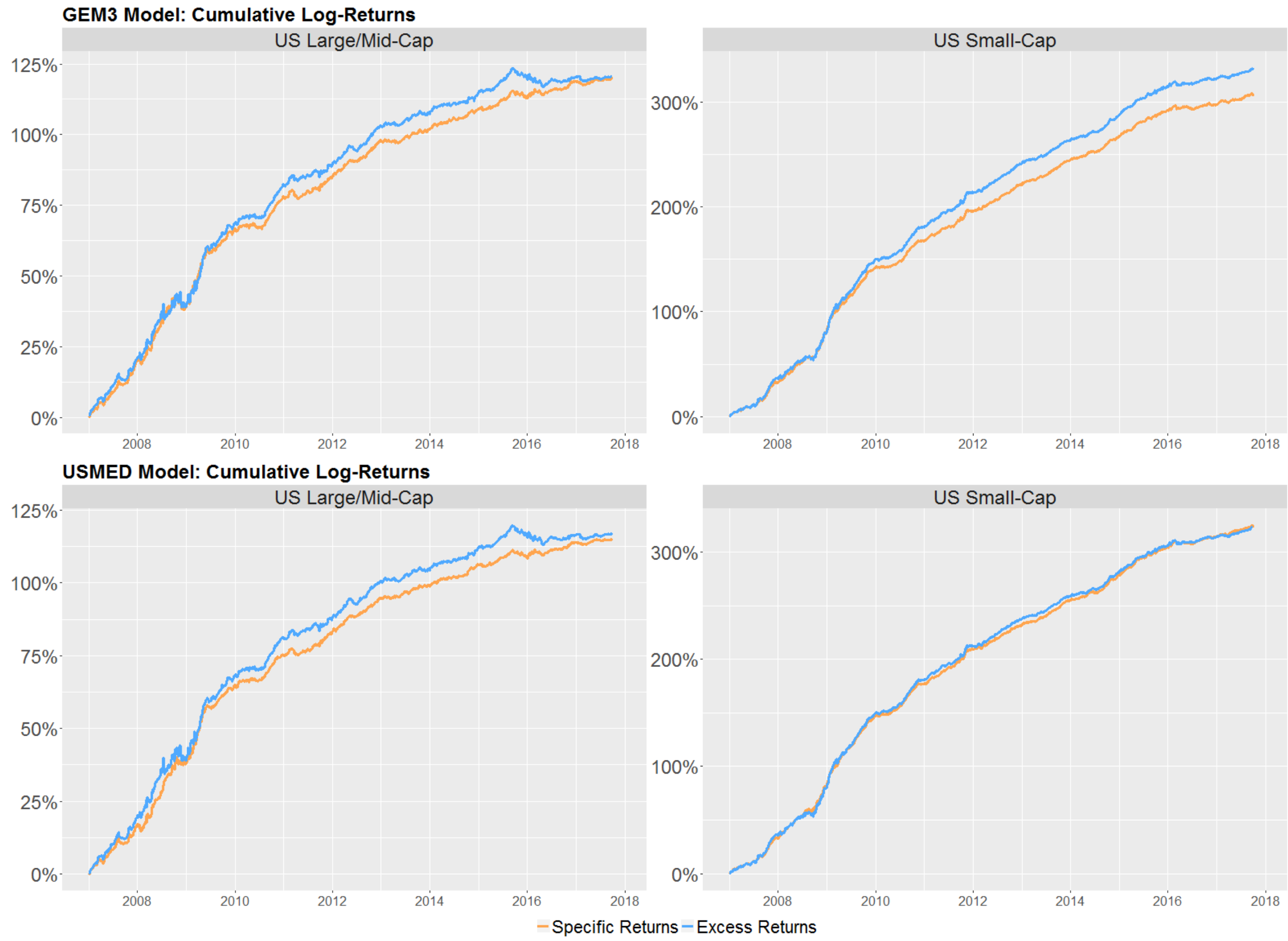

FIGURE B.1: Cumulative Return Profile Comparison across MSCI Models. Comparison between MSCI specific returns and excess returns for a daily strategy on a one-day aggregated RPA signal. Top: MSCI GEM3 model. Bottom: MSCI USMED Model. In both cases, results are shown for U.S. Large/Mid-Cap (left) and Small-Cap (right) universes.

Source: RavenPack, MSCI, October 2017

	GEM3 Model				USMED Model			
	Large/Mid-Cap		Small-Cap		Large/Mid-Cap		Small-Cap	
Statistics	Specific Ret	Excess Ret	Specific Ret	Excess Ret	Specific Ret	Excess Ret	Specific Ret	Excess Ret
Annualized Return	11.02%	11.04%	28.08%	30.50%	10.72%	10.88%	30.07%	30.13%
Annualized Vol.	4.20%	4.52%	5.51%	6.11%	3.47%	4.50%	5.36%	6.12%
Information Ratio	2.63	2.44	5.10	4.99	3.09	2.42	5.61	4.92
Avg. Portfolio Size	188	189	193	192	188	190	194	193
Max. Drawdown	5.14%	6.48%	4.15%	4.42%	2.98%	6.40%	3.25%	4.42%
Turnover	84.8%	83.1%	90.3%	89.5%	84.6%	83%	89.7%	89.5%

TABLE B.1: Experimental Stats. Comparison between MSCI specific returns and excess returns for a set of statistics. Results are shown for GEM3 and USMED models both for Large/Mid-Cap and Small-Cap.

Source: RavenPack, MSCI, October 2017

Appendix C: Statistical Significance Analysis

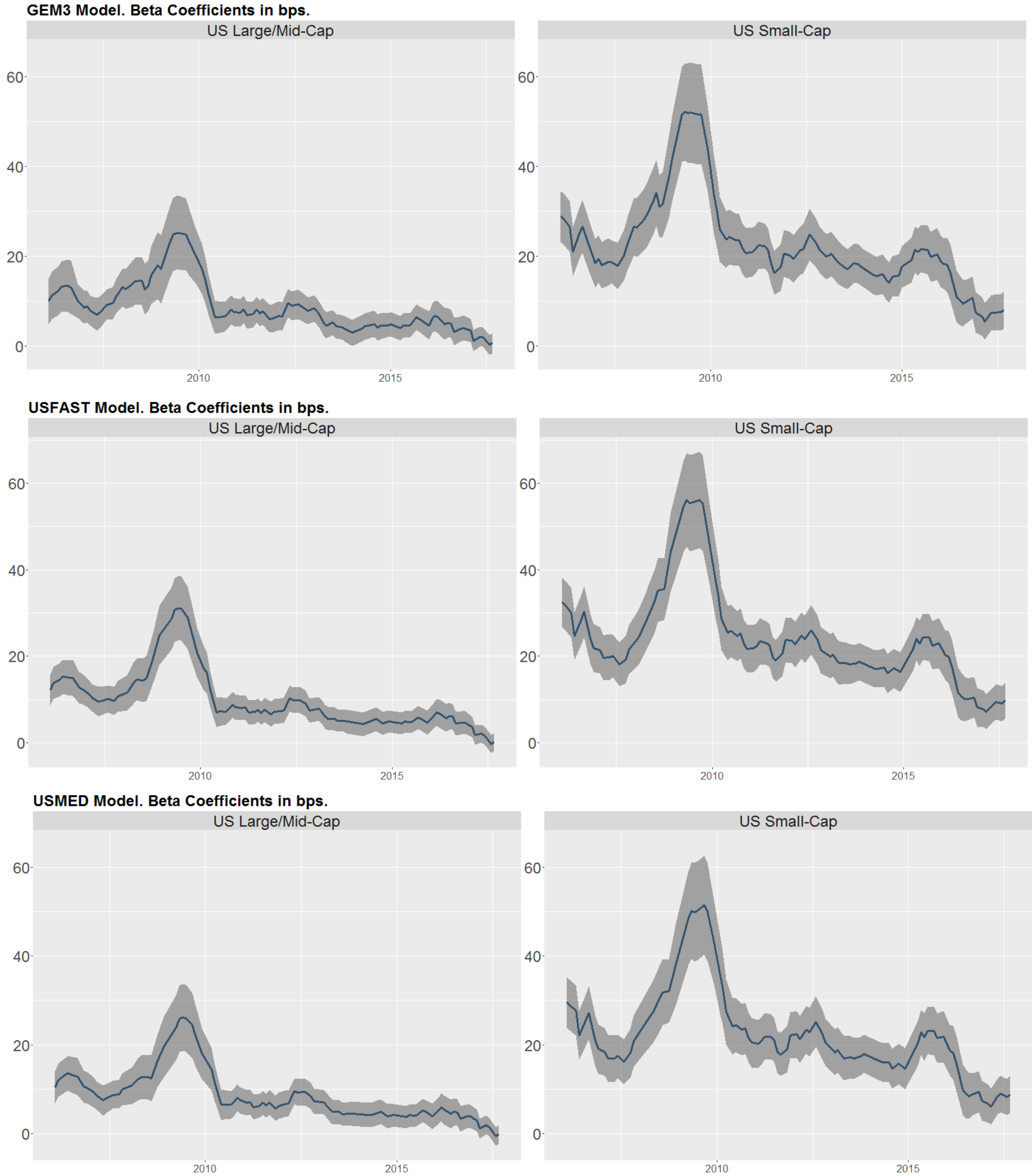

FIGURE C.1: Estimated ESI Coefficient by Market Capitalization Across MSCI Models. GEM3 (top), USFAST (middle) and USMED (bottom) results are shown for Russell 1000 (left) and Russell 2000 (right). Notice that the coefficients (y-axis) are multiplied by 10,000 and can be interpreted as the number of basis points the ESI adds to the overall log-return prediction for a given level of ESI. We can see that for all experiments the coefficients remain significant across time, which confirms the strength of using ESI as a return predictor. Not surprisingly, due to market inefficiencies, the small-cap coefficients are "stronger" than the Large/Mid-Cap ones.

Source: RavenPack, MSCI, October 2017

Appendix D: Predictive Power of Lagged Sentiment

In this paper, we analyze signal decay using aggregation, which effectively has a similar effect to holding the signal for longer. As an alternative, in this appendix, we evaluate the predictive power of lagged sentiment to predict *n*-day ahead returns. By lagging the sentiment by an increasing number of days, we can isolate the signal's effect for each individual day of a multi-day holding period. This enables us to determine the optimal holding period from a signal decay perspective. Figures D.1 and D.2 shows an Information Ratio comparison across different lagged periods for U.S. and Europe, respectively. As a benchmark, we include the sentiment signal for one-day aggregation to predict next-day returns. The x-axis labels represent the number of *additional* days/weeks we have lagged ESI beyond the one-day lag. The "Reference" label corresponds to Equation 1, while the "1 Day" label refers to an ESI variable, which has been lagged by two days relative to the return.

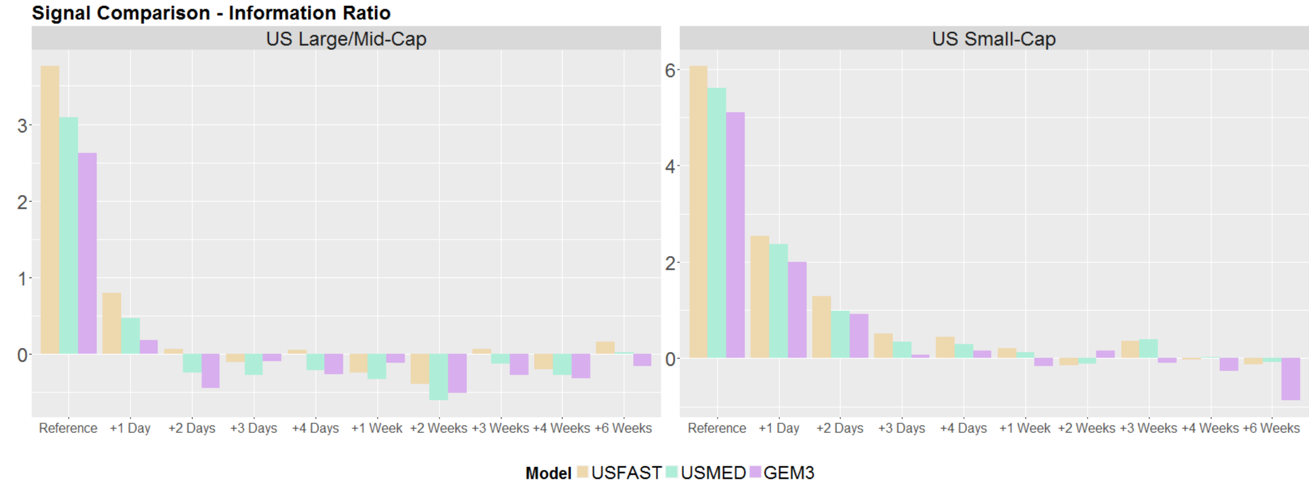

FIGURE D.1: Information Ratio Comparison Across U.S. Models Using Lagged Sentiment. Results are shown for Large/Mid-Cap (left) and Small-Caps (right). We can see that there is stronger predictability for Russell 2000. In contrast, the signal seems to decay after two days on Russell 1000, although it seems to be predictable of a reversal over the following days.

Source: RavenPack, MSCI, October 2017

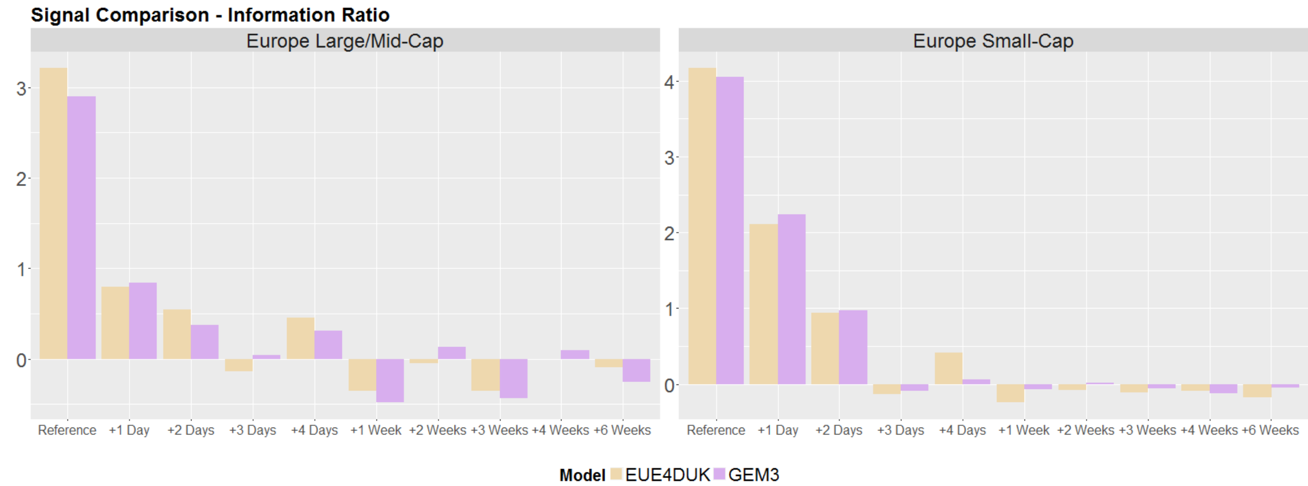

FIGURE D.2: Information Ratio Comparison Across European Models Using Lagged Sentiment. Results are shown for Large/Mid-Caps (left) and Small-Caps (right). We can observe that the IR for Small-Caps decays slower than for Large/Mid-Caps. Similar to the U.S., the signal for Large/Mid-Caps turns into a reversal signal after about 1-week.

Source: RavenPack, MSCI, October 2017

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