MSCI

Research Insight

Systematic Equity Strategies

A Test Case Using Empirical Results from the Japan Equity Market

Mehmet K. Bayraktar

Jyh-Huei Lee

Igor Mashtaler

Nicolas Meng

Jay Yao

Jun Wang

June 2013

Introduction

In an earlier paper,[1] we introduced Systematic Equity Strategies (SES), provided an overview of their characteristics, and presented why it is important that risks associated with exposure to SES factors is quantified and understood by investors.

In this paper, using data from the Japan equity markets, we define seven new SES factors, study their empirical behavior, and show how these factors capture risk in a fundamental factor model.

We present evidence about the role that these factors play in both portfolio construction and risk management. We describe problems associated with omitting these factors from a risk model, and explain why models that include these risk factors should lead to improved portfolio risk forecasts.

Summary of Findings

Using data from the Japanese equity markets, we find:

- Significant crowding risk associated with the SES Factors in Japan.
- A risk model with SES factors provided superior risk forecasts for investment strategies that tilt towards SES factors. Based on bias statistics, a risk model without these factors under-predicted risk by as much as 40 percent across a long history. The risk under prediction has been trending higher since August 2007.
- A risk model with SES factors improved explanatory power in decomposing risk and returns of representative investment strategies. Even for a baseline Large Cap Value and Momentum investment strategy, the SES approach explained more than 10 percent of the variance compared to a standard risk model with Value and Momentum factors.
- Including SES factors in the risk model also helped with construction of index-tracking and minimum volatility portfolios.

We also present descriptive information on the performance of SES Factors in Japan, demonstrating their information decay properties and how they have changed over time, together with seasonality of the factor returns.

In the empirical analysis section of this paper, we present results on:

i) Explanatory power of SES factors
ii) SES factor correlations
iii) A Composite Systematic Equity Strategy
iv) Risk Model Prediction
v) Return Attribution
vi) Portfolio Construction
vii) SES Factor Performance:
    a. Information Decay and Crowding, and
    b. Seasonality and Factor Timing.

[1] Bayraktar, Radchenko, Winkelmann, and Zangari (2013).

We conclude by reviewing our findings and noting that SES Factors are important sources of risk in Japan. We show how we incorporated them alongside traditional Barra risk factors for Japanese equities and how they played a key role in capturing and predicting investment risk in our study.

Systematic Equity Strategies in Japan

In Table 1 we list the individual factors that we considered for each of the systematic equity strategies in Japan.

Table 1: SES Classification.

Systematic Equity Strategies			
Valuation	**Quality**	**Sentiment**	**Momentum**
Value	**Earnings Quality**	**Analyst Estimates**	**Price Momentum**
Book-to-Price	Accruals	Estimate Revisions	Stock Momentum
Dividend-to-Price	Cash Earnings	**Analyst Ratings**	Industry Momentum
Sales-to-Price	Sales Turnover, ROA	Ratings Changes	**Linkages**
Cash Flow to Price	**Financing Quality**		Geographic
Earnings Yield	Composite Issuance		Economic
EBIT/EV	Net Stock Issuance		Analyst Coverage
Fwd E/P	**Management**		**Flows**
	Management Bias		Mutual Fund Flows
	Insider Transactions		**Reversal**
	Investment Decisions		Short- & Long-Term

In determining the final list of factors that went into the risk model, we grouped underlying factors based on their risk and return characteristics. Grouping of factors had several advantages compared to using individual factors as it allowed expansion of the information set without increasing the complexity of the linear factor model, keeping the number of factors the same. It also helped us deal with the problem of multicolinearity in the model. Many individual factors in the sub-strategies were highly correlated. Introducing all individual factors rather than sub-strategies may have created a multicoliniearity problem in the model and compromised the model stability.

Furthermore, the final list of factors depends on data availability. As an example, while we have a data-set unique to Japan that allows us to construct the Management Bias factor, we do not have the corresponding data for Insider Transactions. Therefore, while we were able to incorporate Management Bias into the construction of the Management factor, we were not able to do the same for Insider Transactions.

Below is a list of the final set of Japan SES factors together with a short explanation of how we construct them:

Value:	Composite of Book-to-Price, Dividend-to-Price, Sales-to-Price
Earnings Yield:	Composite of EBIT/EV and Forward E/P
Earnings Quality:	Composite of Accruals and Cash Earnings
Sentiment:	Composite of Consensus Estimate Revisions, Toyo-Keizai Estimates & Rating Changes

Management:	Composite Issuance and Company Management Bias
Stock Momentum:	Simple Stock Momentum (measured over 1 year)
Industry Momentum:	GICS Sub-Industry Momentum (measured over 6 months)
Short-term Reversal:	Simple 1-Month Reversal
Long-term Reversal:	Simple 2-Year Reversal (lagged by 1 year)

Empirical Results

Analysis

We have analyzed the performance of Systematic Equity Strategy (SES) Factors within the context of an equity factor model framework. We summarize details of the empirical analysis in the table below.

Analysis Details

Country:	Japan
Period:	Sep 1992 – Dec 2012
Frequency:	Daily
Return Estimation:	Multivariate regression
Weighting Method:	Square root market capitalization
Factors:	See Model Comparison table

Model Comparison

In order to evaluate the benefits of incorporating SES factors in an equity multi-factor model framework, it is helpful to think about the three versions of risk models introduced in Table 2.

Table 2: Defining Models and Factors.

	Model 1	Model 2	SES Model
Market & Industries			
Size			
Size Non Linearity			
Beta			
Residual Volatility			
Liquidity			
Leverage			
Foreign Sensitivity			
Macro Sensitivity			
Growth			
Stock Momentum			
Value			
Earnings Yield			
Earnings Quality			
Management			
Sentiment			
Industry Momentum			
Long Term Reversal			
Short Term Reversal			

Here, we have treated Price Momentum and Value as separate from the other SES factors.

Price Momentum and Value are two of the SES factors that are used in standard factor models. We think it is helpful to separate their contribution from the rest of the SES factors.

Model 1 excludes all of the SES factors and uses standard risk/control factors.

Model 2 excludes SES factors except for Price Momentum and Value.

The SES Model includes all of the factors.

We found that the average and median adjusted R-squared of the cross-sectional regression went up as we moved from Model 1 to Model 2 to the SES Model (Table 3). While adding Value and Price Momentum increased the average adjusted R-squared from 26.9 percent to 27.2 percent, we found that the remaining SES factors were also significant in explaining the cross-section of stock returns.

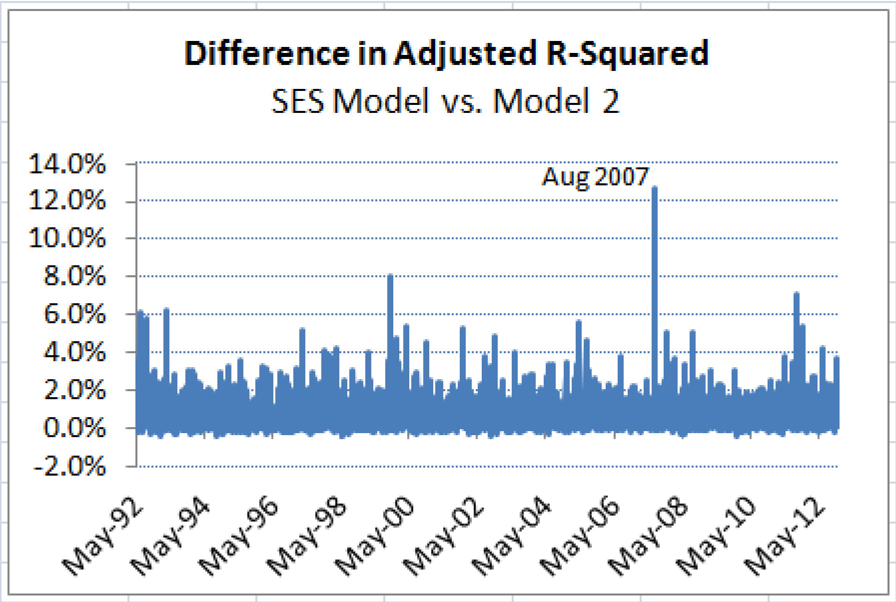
Table 3: Adjusted R-Squared Increased.

Adjusted R-Squared (Sep-92 - Dec-12)

	Model 1	Model 2	SES Model
Mean	26.9%	27.2%	27.9%
Median	22.2%	22.5%	23.3%

Figure 1 plots the time-series of the daily differences in adjusted R-squared between the SES Model and Model 2. It is interesting (though not surprising) to note that August 2007 stood out as a period where this difference was most significant. Including SES factors in the multi-factor model provided an additional 12 percent of explanatory power during this period.

Figure 1: Differences in Adjusted R-Squared Over Time.

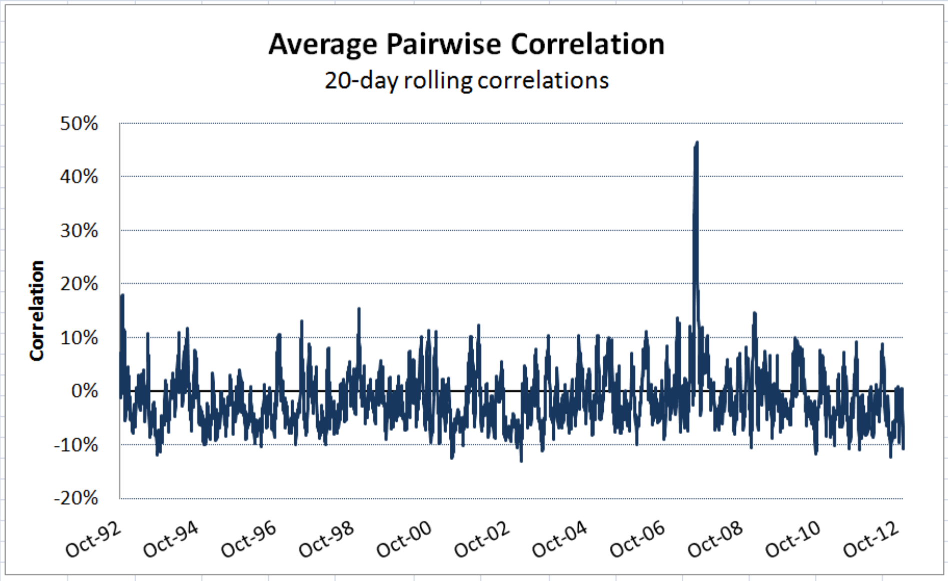


SES Factor Correlations

One concern with including SES factors in a multi-factor setting is that they may overlap with existing factors, thus introducing multi-collinearity in the factor set. In order to measure whether the addition of the SES factors introduces distinct drivers of risk and return, we examined the correlation of realized SES factor returns.

Figure 2 shows the average of pairwise correlations of SES factor returns. While the average correlation of SES factors generally fluctuated around zero percent, we found that during the quant crisis of 2007, the correlations jumped to 50 percent.

Figure 2: Realized Pairwise Correlation of SES Factors.



Composite Systematic Equity Strategy

The correlation spike during the Quant Crisis of August of 2007 initiated further analysis because it may have been caused by unwinding of the crowded positions. To illustrate the magnitude of crowding, we formed a composite of systematic equity strategies by taking a linear combination of the underlying strategies.[2]

In the chart below, we show cumulative returns of this strategy using three investment universes:

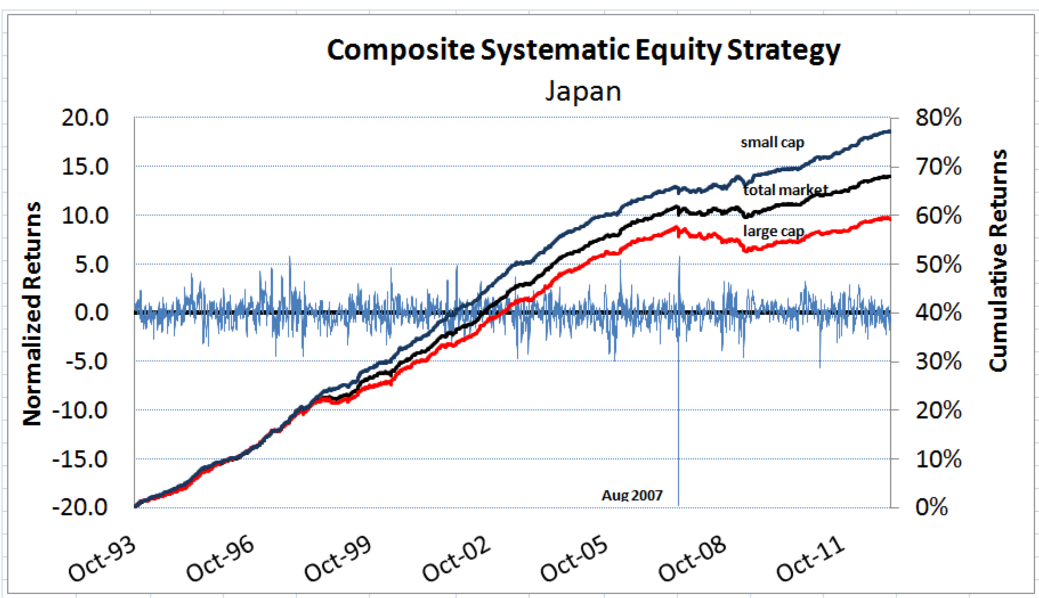
1. Large cap (red line),
2. Small cap (blue line), and
3. Total market on the right axis.

We also plotted the rolling weekly normalized returns series of the strategy formed using the total market (left axis, light blue line).[3]

While this composite strategy had a much steeper slope during the early part of the sample, since 2002 there was a visible degradation in performance. Using the small cap universe generated the best returns without an adjustment for transaction costs.

We also saw that during the quant crisis of 2007, this strategy experienced close to a -20 standard deviation normalized weekly return with only partial recovery during the following week.

Figure 3: Composite Strategy Performance.



We believe that these combined systematic strategies can be useful in attributing what investors experienced during the Quant Crisis in 2007. Furthermore, there seemed to be significant risks related

---

[2] More specifically, we form an inverse variance weighted linear combination of long-short factor portfolios representing each SES factor. We find that the results were not too sensitive to the weighting scheme used in constructing the composite strategy.

[3] We normalize returns by dividing weekly returns of the strategy by trailing 6-month volatility.

to the implementation of these strategies that may have exhibited itself as extreme risk during crisis periods.

Risk Model Prediction and SES Factors

While it is noteworthy to see the performance of the composite SES strategy during the Quant Crisis of 2007, we needed to confirm that the inclusion of SES factors in the risk model increased the accuracy of the risk forecasts.

To gain insight into the performance of the three models, we measured the forecasting accuracy in predicting risk for three large cap composite strategies:

1. Strategy I: Large Cap Composite Value & Momentum Strategy
2. Strategy II: Large Cap Composite SES Strategy including Value & Momentum
3. Strategy III: Large Cap Composite SES Strategy excluding Value & Momentum

The following table summarizes the Bias and Q Statistics of the three models:[4]

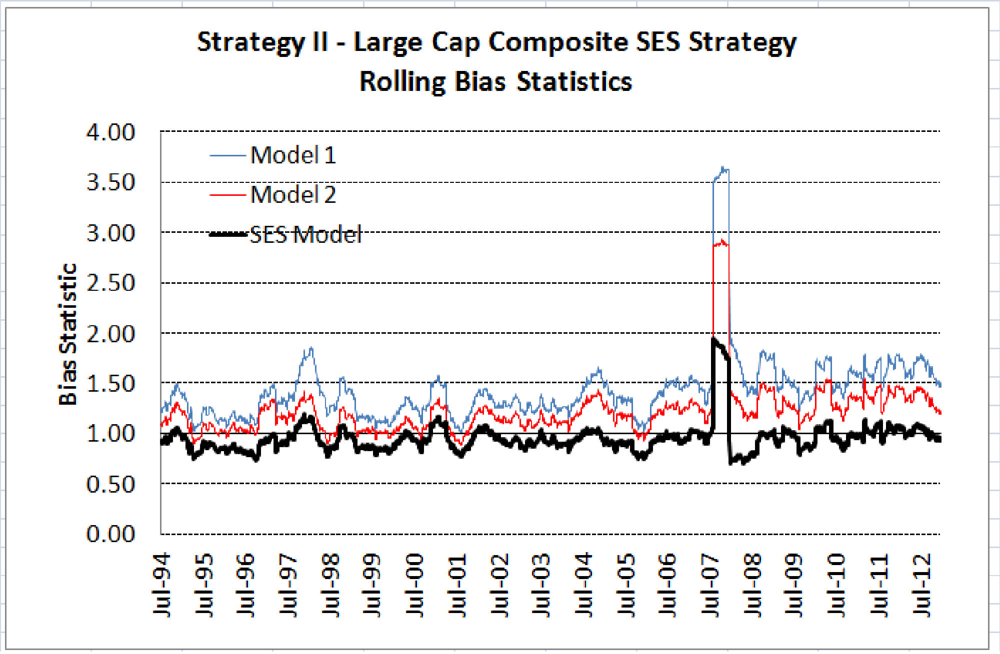
Table 4: Forecasting Accuracy.

		Model 1	Model 2	SES Model
Strategy I	Bias	1.42	0.96	0.96
	Q	2.70	2.37	2.37
Strategy II	Bias	1.50	1.27	0.98
	Q	2.87	2.52	2.33
Strategy III	Bias	1.34	1.34	0.92
	Q	2.60	2.61	2.34

We found that the SES Model provided the most accurate risk forecasts based on both Bias and Q statistics when measured from January 1994 to December 2012. The following chart illustrates the time-series dynamics of the rolling bias statistics for Strategy II. Since the Quant Crisis, both Models 1 and 2 have seen consistently higher bias statistics (bias statistics above 1.00 indicate under prediction), which translated into significant under prediction of risk for the Large Cap Composite SES Strategy that included Value and Momentum factors.

[4] We offer an explanation of the Q statistic in Appendix B.

Figure 4: Persistent Under-Prediction of Risk with Models 1 and 2.



Return Attribution and SES Factors

Next, we analyzed the return attribution properties of the three models. Table 5 below summarizes the realized variance decomposition of Strategies I, II, and III.

We found that for Strategy I, where Value and Momentum factors were common to both Model 2 and the SES Model, the explanatory power of the two models are closest at 67 percent and 77 percent, respectively. For Strategy II, which included other SES factors that are not captured by Model 2, the variance decomposition indicated that only 22 percent of realized returns were explained by factors in Model 2, while the rest were assigned to Stock Specific (or Residual).

For Strategy III, where we used all SES factors, excluding Value and Momentum, we found that only 2 percent of the returns were explained by Models 1 or 2.

In all the comparisons, we found that the SES Model was able to explain a significantly larger portion of the strategy returns with all factors (unlike Models 1 and 2).

Table 5: SES Model Improved Attribution Results.

Return Attribution - Variance Decomposition (Jan 94 - Dec 12)

		Model 1	Model 2	SES Model
Strategy I	Factors	1%	67%	77%
	Stock Specific	99%	33%	23%
Strategy II	Factors	5%	22%	83%
	Stock Specific	95%	78%	17%
Strategy III	Factors	2%	2%	84%
	Stock Specific	98%	98%	16%

Portfolio Construction

So far, we have demonstrated the benefits of including SES Factors in the risk model by examining the performance of risk models used to explain or predict risk of *existing* portfolios. In this section, we examine the properties of these risk models used in *constructing* portfolios. We considered three portfolio construction scenarios:

i) SES Alpha Portfolio

ii) Index Tracking Portfolio

iii) Minimum Volatility Portfolio

SES Alpha Portfolio

We analyzed the performances of SES Model and Model 2 in constructing SES Alpha Portfolios in a backtest analysis framework. We specified the backtest parameters as shown in Table 6 below. The backtest returns do not include transaction cost estimates. We constrain turnover of the strategy to 3% per rebalance and limit the investment universe to stocks in MSCI Japan IMI index. Figure 5 plots the realized annualized returns and tracking errors of backtest portfolios using Model 2 and the SES Model. Each dot on the lines correspond to a backtest portfolio with a variance aversion parameter. We observed that the portfolios constructed with the SES model had higher realized returns for a given level of realized tracking error.

Table 6: SES Alpha Portfolio Backtest.

Alpha:	SES Strategy
Period:	Sep 1992 – Dec 2012
Benchmark:	MSCI Japan IMI
Strategy:	Long-Only
Rebalance:	Weekly
Turnover:	3% per week
Asset Weight:	<+/-5 %

Figure 5: Realized Returns and Tracking Errors.

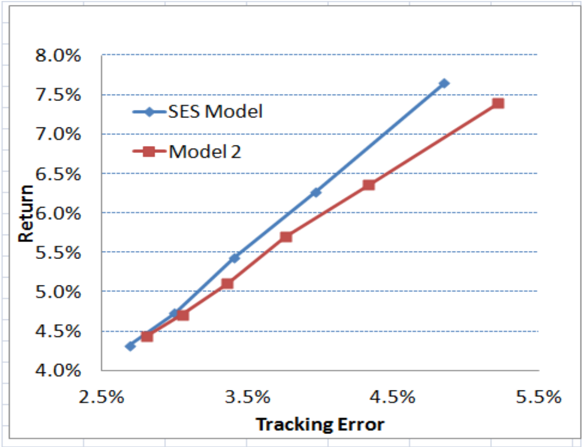


Table 7 provides a summary of the backtest results for two comparable backtest portfolios using SES Model and Model 2. We find that the Bias and Q statistics also favored the SES Model with SES Model producing a lower Bias (1.10 vs. 1.26) and a lower Q (2.41 vs. 2.51).

Table 7: SES Alpha Portfolio Backtest Summary.

	Ret	TE	IR	Pred. TE	Bias	Q	# of Stocks	Turn over
Model 2	5.11%	3.36%	1.52	2.64%	1.26	2.51	144	3.0%
SES Model	5.44%	3.41%	1.60	3.08%	1.10	2.41	145	3.0%

Index Tracking Portfolio

When constructing an optimal portfolio following SES strategy, it was informative to see how the SES model performed better than a model without the SES Factors; however, one of the key determinants of the robustness of the risk model is how it performed when building an Index Tracking portfolio.

We analyzed the performances of risk models in constructing Index Tracking portfolios in a backtest analysis framework. We specified the backtest parameter in Table 8 below.

Table 8: Index Tracking Portfolio Backtest.

Alpha:	No Alpha
Period:	Sep 1992 – Dec 2012
Benchmark:	MSCI Japan IMI
Strategy:	Long-Only, Index Tracking
Names:	max @ 100, max @ 150
Rebalance:	Weekly
Turnover:	2 % per week
Asset Weight:	<+/-5 %

Table 9 provides a summary of the backtest results for backtest portfolios using the SES Model and Models 1 and 2. We find that the realized tracking error of the Index Tracking portfolio was slightly lower using SES Model vs. either model 1 or 2. Bias and Q statistics also favored the SES Model for both scenarios we considered (with 100 and 150 maximum number of names constraints).

Table 9: Index Tracking Portfolio Backtest Summary.

	# of Names	Tracking Error	Bias	Q	Turnover
Model 1	100	1.82%	1.11	2.42	1.71%
Model 2	100	1.81%	1.09	2.30	1.76%
SES Model	100	1.71%	1.06	2.25	1.91%
Model 1	150	1.41%	1.20	2.45	1.67%
Model 2	150	1.38%	1.21	2.47	1.70%
SES Model	150	1.36%	1.15	2.45	1.91%

Minimum Volatility Portfolio

Minimum Volatility portfolio construction is another key determinant of the robustness of the SES risk model.

We analyzed the performance of risk models in constructing Minimum Volatility portfolios in a backtest analysis framework. We specified the backtest parameters in Table 10 below.

Table 10: Minimum Volatility Portfolio Backtest.

Alpha:	No Alpha
Period:	Sep 1992 – Dec 2012
Benchmark:	Cash
Strategy:	Long-Only, Minimum Volatility
Beta:	min 0.5
Rebalance:	Weekly
Turnover:	2 % per week
Asset Weight:	<+/-5 %

Table 11 provides a summary of the backtest results for portfolios using the SES Model and Models 1 and 2. We found that the realized volatilities and Bias and Q Statistics of the Minimum Volatility portfolios were very close all three models.

Table 11: Minimum Volatility Portfolio Backtest Summary.

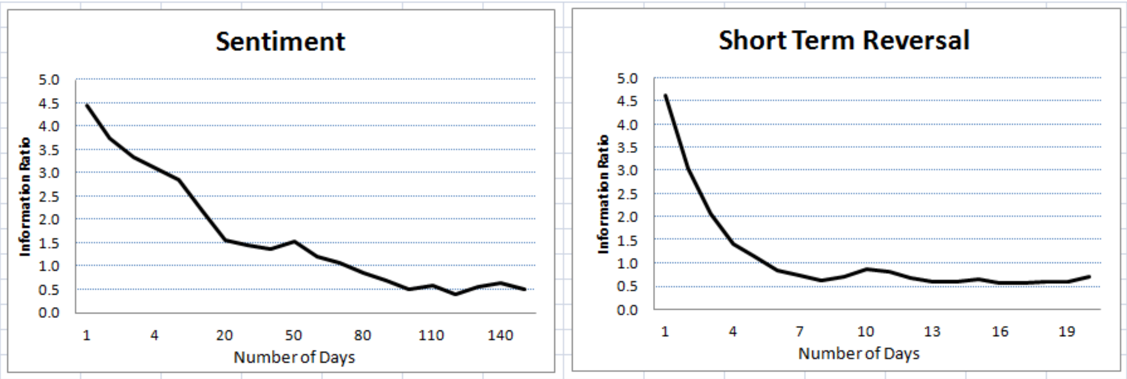
	# of Names	Volatility	Bias	Q	Turnover
Model 1	262	12.29%	1.28	2.69	3.1%
Model 2	255	12.26%	1.26	2.69	3.1%
SES Model	248	12.24%	1.26	2.65	3.1%

Information Decay and Crowding

An interesting observation is the decay of investment information in the SES factor porfolios. To calculate the information content of a factor portfolio across time, we used a factor portfolio constructed on a fixed model estimation date and computed its portfolio returns over a period of lagging dates. By repeating this process over different model estimation dates, we generated a time series of factor returns for each lag. We then computed the factor annualized Information Ratio for each lag.

Figure 6 shows the information ratio as a function of lags measured in trading days. As expected, we found that the SES factors expressed information decay behavior as investors reacted to the information and the strategy was exploited through time. Using Sentiment and Short-Term Reversal factors as examples, we observed that their information ratios decreased as lag increased. For Short-Term reversal the decay happened much more rapidly than for the Sentiment factor, quickly eliminating all outperformance. Sentiment has much longer-lived information content with a 0.5 information ratio still achievable six months after portfolio formation. This indicated that when a strategy factor (or information) was more recent, the return prediction power was at its strongest; the longer the delay to implementation, the lower the prediction power.

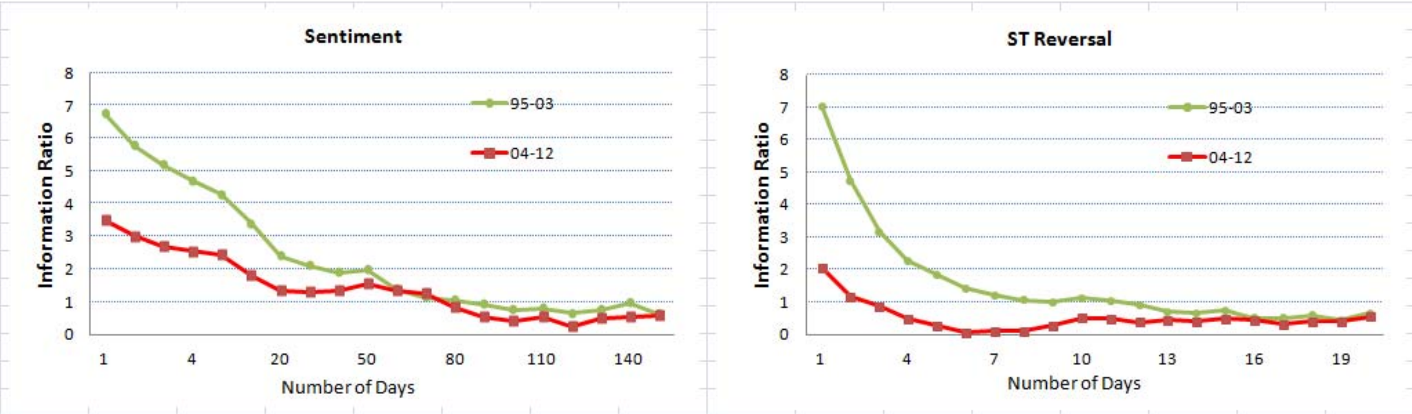
Figure 6: Information decay with lags, using Sentiment and Short-Term Reversal factors as examples.



Furthermore, other factors showed a decay of information over time. This phenomenon indicated that as more and more investors followed the same strategy it may have resulted in diminished return opportunities; in other words, the SES factors became crowded. On the other hand, this could also have been due to faster information diffusion or reduced costs of arbitrage (trading costs) between the two periods.

We again used Sentiment and Short-Term Reversal as examples. Figure 7 shows how the information ratio declined over two distinct time periods. We again observed the information decay through time for the selected periods; however, the levels of information ratio were significantly different between periods. In both cases, the information ratio was lower in the more recent period of 2004 to 2012.

Figure 7: Decay of information over time, using sentiment and short-term reversal factors as examples.



Seasonality and Factor Timing

Performance and volatility of many of the SES factors expressed seasonal behavior in Japan. On the performance side, this suggested the possibility of factor timing. On the risk modeling side, this extra information allowed us to better estimate factor risks.

Table 12 shows summary statistics by quarter for the SES Factors in this study. The factor volatility in first quarter and fourth quarter of a year tended to be higher than second and third quarters.

Moreover, performance was also affected by seasonality with the SES Factors being less effective in the fourth quarter compared to the rest of the year.

Table 12 also shows the weekly returns (in standard deviations) of SES factors during the second week of August 2007 (column Aug '07). We find that Value, Earnings Yield, Earnings Quality, Management, Sentiment, and Stock Momentum factors have experienced multi-sigma negative returns.

Table 12. Factor summary statistics by quarter.

Multi-Variate Regression Results: 09/30/1992 - 12/31/2012

Total Market Universe	Full Period				Volatility by Quarter				IR by Quarter			
	Ret	Vol	IR	Aug '07	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Value	0.7%	2.1%	0.3	(7.7)	2.2%	2.0%	2.0%	2.1%	0.4	0.4	0.2	0.3
Earnings Yield	3.2%	1.7%	1.9	(13.1)	1.8%	1.7%	1.7%	1.7%	1.4	3.0	2.2	0.9
Earnings Quality	1.2%	1.5%	0.8	(3.8)	1.6%	1.4%	1.4%	1.6%	1.2	1.2	0.2	0.4
Management	1.1%	1.4%	0.8	(3.5)	1.5%	1.3%	1.3%	1.4%	0.6	1.4	1.0	1.2
Sentiment	8.3%	1.6%	5.0	(10.7)	1.7%	1.4%	1.6%	1.8%	5.9	6.5	3.6	4.5
Stock Momentum	1.5%	3.3%	0.4	(4.9)	3.7%	3.1%	2.7%	3.3%	(1.4)	(0.1)	2.7	1.0
Industry Momentum	3.6%	1.2%	3.0	0.3	1.3%	1.1%	1.2%	1.3%	2.9	2.8	3.5	2.8
Long Term Reversal	2.9%	2.0%	1.5	2.6	2.1%	1.9%	1.8%	2.1%	3.1	2.1	0.3	0.5
Short Term Reversal	11.8%	2.4%	4.8	3.1	2.6%	2.1%	2.1%	2.8%	5.9	5.7	4.9	4.0

* returns and volatility figures are annualized

** Aug '07 refers to the weekly normalized returns of factors during the week of quant crisis in August 2007

Conclusion

In this paper, we illustrated risk and return properties of SES factors using the Japan equity market as an example. We demonstrated how factors based on Systematic Equity Strategies can be used to better understand and monitor sources of risk and return in equity portfolios.

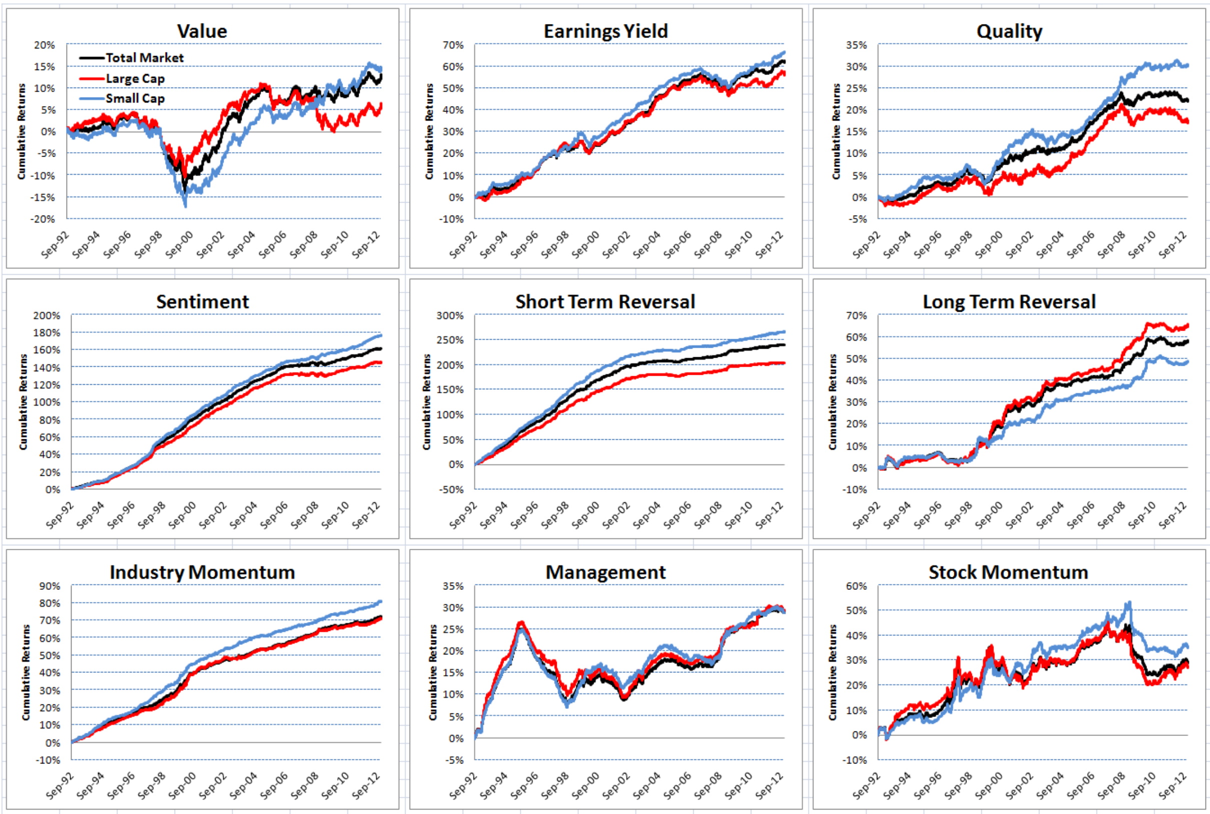
We have shown results from Japan equity markets that highlighted the significance of crowding risk associated with these factors, and how a risk model with these factors produced more accurate risk forecasts.

We also illustrated the benefits of incorporating SES factors in a risk model from a portfolio construction perspective. We have demonstrated that a risk model including SES factors not only improved results for portfolios that are designed to tilt towards the underlying SES strategies, but also with portfolios that tend to be sensitive to errors in risk model estimation.

These results illustrate how there may be significant benefits to incorporating SES factors in Japan equity risk models.

Appendix A: SES Factor Performance

Figure 8. Cumulative performance of factors estimated with total estimation universe, large capitalization universe and small capitalization universe.



Appendix B: Q Statistics

Patton (2011) describes measures of forecast accuracy in terms of "loss functions." He defines a loss function as "robust" if the ranking of any two volatility forecasts by expected loss is the same whether the ranking is done using the true variance (unobservable) or some unbiased variance proxy (e.g., squared return). One example of a robust loss function is the Q-statistic, defined for portfolio n and time t as

$$Q_{nt} = z_{nt}^2 - \ln(z_{nt}^2)$$

Patton further shows that the Q-statistic is the unique loss function (up to trivial additive and multiplicative constants) that depends solely on standardized returns (i.e., z-scores). This makes the Q statistic ideal for evaluating risk model accuracy, because it places every observation on an equal footing (whether the volatility is high or low).

If returns are normally distributed, the expected value of the Q-statistic is approximately 2.27.

References

Bayraktar, M. K., S. Radchenko, K. Winkelmann, and P. J. Zangari (2013). "Employing Systematic Equity Strategies," MSCI Research Insight.

Patton (2011). "Volatility forecast comparison using imperfect volatility proxies", *Journal of Econometrics*, doi:10.1016/j.jeconom.2010.03.034.

Client Service Information is Available 24 Hours a Day

clientservice@msci.com

Americas

Americas	1.888.588.4567 (toll free)
Atlanta	+ 1.404.551.3212
Boston	+ 1.617.532.0920
Chicago	+ 1.312.675.0545
Montreal	+ 1.514.847.7506
Monterrey	+ 52.81.1253.4020
New York	+ 1.212.804.3901
San Francisco	+ 1.415.836.8800
Sao Paulo	+ 55.11.3706.1360
Stamford	+1.203.325.5630
Toronto	+ 1.416.628.1007

Europe, Middle East & Africa

Cape Town	+ 27.21.673.0100
Frankfurt	+ 49.69.133.859.00
Geneva	+ 41.22.817.9777
London	+ 44.20.7618.2222
Milan	+ 39.02.5849.0415
Paris	0800.91.59.17 (toll free)

Asia Pacific

China North	10800.852.1032 (toll free)
China South	10800.152.1032 (toll free)
Hong Kong	+ 852.2844.9333
Seoul	00798.8521.3392 (toll free)
Singapore	800.852.3749 (toll free)
Sydney	+ 61.2.9033.9333
Tokyo	+ 81.3.5226.8222

Notice and Disclaimer

About MSCI

MSCI Inc. is a leading provider of investment decision support tools to investors globally, including asset managers, banks, hedge funds and pension funds. MSCI products and services include indices, portfolio risk and performance analytics, and governance tools.

The company's flagship product offerings are: the MSCI indices with close to USD 7 trillion estimated to be benchmarked to them on a worldwide basis[1]; Barra multi-asset class factor models, portfolio risk and performance analytics; RiskMetrics multi-asset class market and credit risk analytics; IPD real estate information, indices and analytics; MSCI ESG (environmental, social and governance) Research screening, analysis and ratings; ISS governance research and outsourced proxy voting and reporting services; and FEA valuation models and risk management software for the energy and commodities markets. MSCI is headquartered in New York, with research and commercial offices around the world.

[1] *As of September 30, 2012, as published by eVestment, Lipper and Bloomberg on January 31, 2013* *Apr 2013*