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Exploring Alpha from the Securities Lending Market

New Alpha Source Stemming from Improved Data

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Numerous studies have examined the information content of short interest and found that heavily shorted stocks tend to underperform and liquid stocks with low levels of short interest subsequently outperform. Most studies relied on short interest data obtained directly from the exchanges available with a significant delay.

S&P Capital IQ has partnered with Data Explorers, an innovative data company that provides content on the securities lending market including daily shares borrowed, inventory of available shares on loan, and stock borrowing costs. We examine the usefulness of this unique data set in the U.S and other international developed markets, and find that this timelier, daily data provides additional signal strength over the traditional lagged data sourced from the exchanges. Our results are robust to shorting cost adjustments and over geography:

- **Using Data Explorers Securities Lending Data we construct alpha signals which deliver statistically significant return spreads.** We build factors that fall into 5 general categories: Supply, Demand, Cost, Utilization, and Special factors. Sixteen out of the nineteen factors have annualized return spreads of over 16% between July 2006 and October 2011 among Russell 3000 companies (Table 1), with a majority statistically significant at the 5% level.

- **Employing a simple equal-weighted five-factor strategy we generate an annualized long-short return spread and information ratio of 41% and 1.91 respectively** using the Russell 3000 index from July 2006 to October 2011.

- **The return spread of the U.S model remains economically significant after adjusting for cost to borrow and a minimum $5 share price filter.** The annualized return is 27.9% compared to the original model of 41% (Table 4).

- **We construct similar multi-factor strategies for other developed markets and observe similar statistically significant return spreads.** The annualized return spreads are 38.8%, 36.3%, and 37% in Canada, Europe and Asia respectively.

- **The Securities Lending Market Model (SLM) is complementary to existing alpha strategies.** Combining the SLM with S&P Capital IQ's Stock Selection Models (Value, Growth, Quality), we see improvements of 49% (Value), 63% (Growth), 97% (Quality) in annualized return and 34%, 41%, 68% in information ratio respectively.

1. Introduction

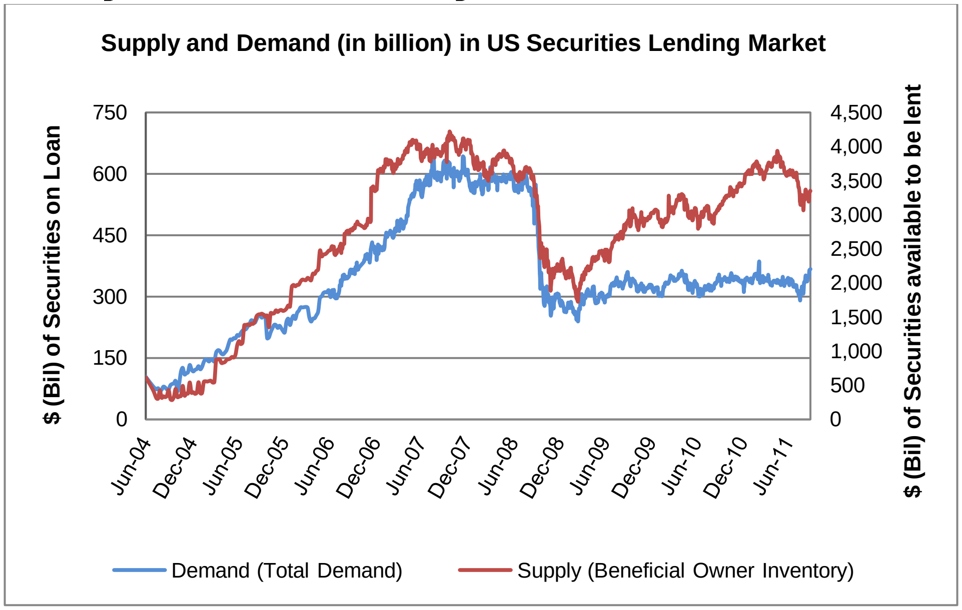
The benefits of short selling have been widely recognized by regulators, market participants and academics. As stated by IOSCO (The International Organization of Securities Commissions) in its 2009 paper: 'short selling plays an important role in the market for a variety reasons, such as providing more efficient price discovery, mitigating market bubbles, increasing market liquidity, facilitating hedging and other risk management activities'. In a short selling transaction, the seller typically has to borrow the security to be shorted. Therefore, the securities lending market provides important information on short selling activities.

There is an extensive body of research on the relationship between short interest/security lending and future stock return. In general, there are three different views on this relationship. The first is represented by the rational expectation model developed by Diamond and Verrechia (1987), which suggests that increases in short interest is bad news and only informed investors conduct short selling. Other empirical researches that support this view include Asquith and Meulbroek (1995), Hong and Stein (2003) and Sorescu (2007). The second view contends that high short interest is a bullish signal. According to Epstein (1995), short interest represents future demand because of close of a position, therefore a relatively high short interest is a bullish signal. Boehmer, Huszar, and Jordan (2009) also suggest that there is a positive relationship between short interest and future stock performance. Boulton and Braga-Alves (2009) document a positive market reaction to announcements of increased level of naked short selling. The last view suggests that short interest is a neutral indicator; short sellers are not more informed than other investors and short interest data cannot be used as a reliable indicator of subsequent returns. This view is supported by the research of Brent et al (1990) and Chen et al (2002).

This report examines the relationship between security lending data, collected and distributed by Data Explorers ("DX"), and future stock returns. The securities lending data act as a proxy for short selling activities. Unlike exchange data which is published twice a month, DX's data is published daily, thus providing a timely view of the dynamics in the securities lending market.

Figure 1 shows the daily dollar value of securities available to be lent (red line, scaled to the right), a proxy for supply, and the dollar value actually on loan (blue line, scaled to the left), a proxy for demand, in the U.S market. The recent global financial crisis has had a clear impact on securities lending. The daily value of securities lent in the U.S peaked at $650 billion in 2007 and dropped sharply in the second half of 2008 at the height of the financial meltdown and restriction of short-selling activities. It has stabilized at around $300 billion in recent months; around half of what it was at its peak. The daily supply follows a similar pattern, although the dollar amount available for lending is much higher than the demand. Supply has gradually risen back to 2007 levels since the precipitous decline in 2009.

Figure 1 – U.S Securities Lending Market: June 2004 – October 2011



2. Data and Universe Definition

Most of the publicly available empirical research on short-selling is conducted using short interest data from U.S stock exchanges (NYSE, NASDAQ, and AMEX). The exchange data is published twice a month based upon mid-month and end-of-month settlement dates, with about 10 days lag after broker-dealers report their positions. This single data point with low frequency fails to paint a complete picture of the entire securities lending market. According to Cohen, Diether, and Malloy (2007), many short sellers cover their positions very rapidly, with about 50% of securities lending contracts closed within two weeks of being opened. Data Explorers' Securities Lending database addresses these deficiencies by providing subscribers with a data set that covers demand, supply and cost of borrowing in daily securities lending activities. Data is available from June 2004 and is collected globally. We provide a comprehensive introduction to the DX data set and the steps we took to clean the data in Appendices A and B respectively.

Data Explorers (DX) collects data throughout the day directly from various sources, including prime brokers, custodians, asset managers and hedge funds. DX reports on over 3 million intraday transactions, covering $12 trillion of securities in the lending program of 20,000 institutional funds. Currently, the company covers more than 85% of global securities lending transactions. There are over five years of daily historical data (from July 2006) and an additional two years of weekly data (from August 2004).

Due to regulatory policy constraints and data coverage, our analysis covered United Kingdom, France, Italy, Sweden, and Switzerland in Europe; Japan, Australia, Hong Kong, and Singapore in Asia; and U.S and Canada in North America. Our study universe used the BMI index for each county or region, except for the U.S where we used the Russell 3000 index.

Figure 2 shows coverage for the number of securities on loan in the U.S, Canada, Europe and Asia as a proportion of the number of securities in the respective index (Russell 3000 or BMI) over time. We observe broad coverage in North America and BMI developed countries in Europe and Asia.

Figure 2 – Coverage for Number of Securities on Loan in Global Markets: June 2004 – October 2011

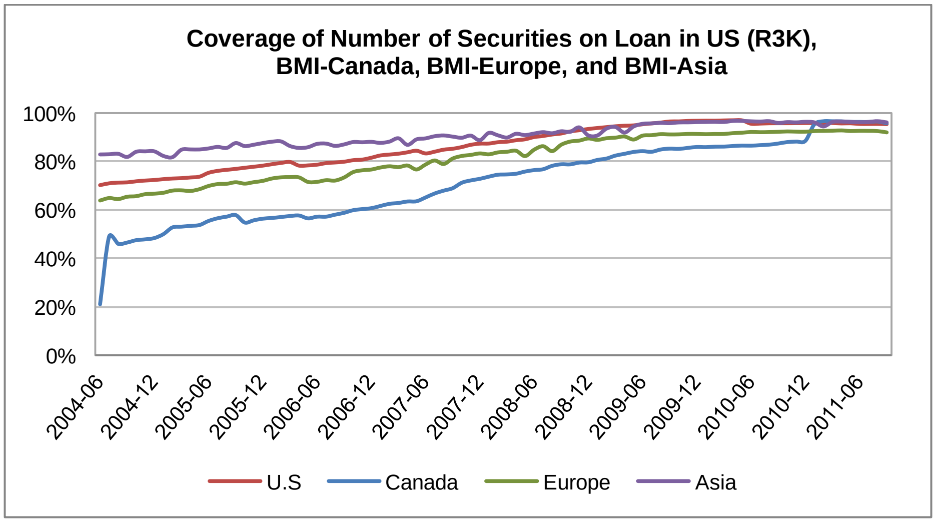
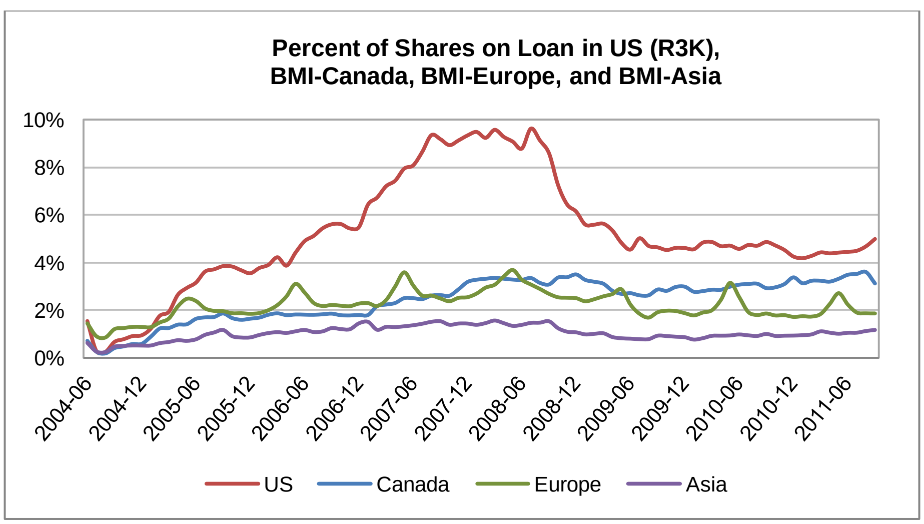


Figure 3 shows the percent of shares on loan (shares on loan divided by shares outstanding) for North America, Europe, and Asia. The securities lending market is obviously more active in the U.S compared to other markets as depicted by the red line. At its peak in 2007, there were roughly three times more shares on loan as a proportion of shares outstanding in the U.S than in any other market. The percent of share on loan is lowest in Asia across time, suggesting that investors are less willing to take short positions, or are constrained by regulatory reasons.

Figure 3 – Shares on Loan/Shares Outstanding in Global Markets: June 2004 – October 2011



3. Factor Formulation and Testing

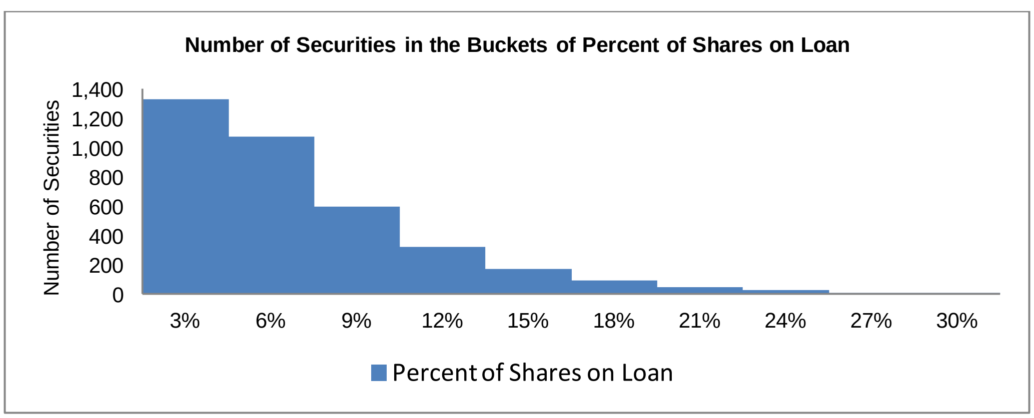
We grouped the factors we tested into five broad categories:

- Demand: Demand is the quantity on loan. Securities with high demand have a higher level of shares on loan compared to securities with low demand. According to the rational expectations model, stocks with high demand ratios should underperform those with low ratios.
- Supply: Supply is the quantity of shares available to be borrowed. Limited supply can be an indication that a security is difficult to borrow, which leads to a tighter constraint on short-selling. Diamond and Verrechia (1987) suggest that such constraint reduces the adjustment speed of prices to bad news.
- Utilization: Utilization factors measure the relationship between demand and supply; these signals provide an insight into how the interplay of demand and supply affects stock price movements.
- Cost: High borrowing cost is a key constraint in short-selling. A security can have a high cost to borrow due to limited supply (low institutional ownership) or high demand.
- Special Factors: These are DX-provided factors and are intended to measure a security's market sentiment. DX indicators are derived from securities lending data and stock price information.

We provide a detailed factor classification and definition in Appendix C.

We tested our factors on a weekly basis, which enables us to incorporate information at twice the rate possible with stock exchange short interest data, but avoids the excessive trading costs associated with daily rebalancing. An examination of our underlying data shows that most of the data items are skewed. For example, Figure 4 demonstrates that shares on loan as a percentage of shares outstanding in the U.S market, is highly skewed to the right. Accordingly, our analysis focuses on the top and bottom 4% of our data distribution. For the Russell 3000, this will be approx 8% of the index, with the top 4% (least shorted) split into two fractiles (Q1 and Q2) and the bottom 4% (most shorted) split into another two fractiles (Q4 and Q5).

Figure 4 – Histogram of Shares on Loan as Percent of Shares Outstanding for Russell 3000: June 2004 – October 2011



3.1 Single Factor Tests

Table 1 shows test results for some of the factors we constructed (refer to Appendix D for a complete description of these factors). The weekly back tests are from July 2006 to October 2011 and were conducted over the Russell 3000; tailed results are based off the top and bottom 4% of factor scores. Results are displayed by the five categories discussed earlier and ordered by the tailed weekly spread return (right half of the table).

Table 1 – Performance Report for Weekly Backtested Factors; Universe: Russell 3000; Time Period: July 2006 – October 2011

Factor Category	Russell 3000				Top/Bottom 4% of Russell 3000			
	Average IC	IC T-stat	T/B Spread	Spread T-stat	Average IC	IC T-stat	T/B Spread	Spread T-stat
Demand								
DCR(TDQ)	0.024	3.90	0.27%	2.68	0.060	5.77	0.36%	2.20
DCR(BOOL)	0.023	3.75	0.26%	2.51	0.060	5.67	0.36%	2.22
SIRatio(TDQ)	0.018	3.20	0.19%	1.83	0.053	5.74	0.36%	2.17
SIRatio(BOOL)	0.018	3.12	0.19%	1.87	0.052	5.46	0.31%	1.91
Supply								
ShareAvailabletoBorrow/SOS	0.024	5.87	0.04%	0.52	0.067	10.82	0.31%	2.25
ActiveAvailableBOInventQty/SOS	0.019	4.97	0.01%	0.10	0.058	10.15	0.29%	2.43
ShareAvailabletoBorrow/AMTV	0.011	1.69	-0.03%	-0.23	0.062	6.52	0.23%	0.97
ActiveAvailableBOInventQty/AMTV	0.007	1.10	-0.04%	-0.36	0.050	5.58	0.02%	0.09
Cost								
CosttoBorScore	0.340	71.96	1.00%	4.01	0.443	48.00	1.22%	2.69
vwafallScore	0.327	71.74	0.60%	4.30	0.437	170.88	0.52%	4.16
vwaf60DScore	0.314	65.31	0.59%	4.32	0.428	151.02	0.50%	4.14
vwaf30DScore	0.308	62.68	0.57%	4.27	0.424	142.00	0.47%	4.14
Utilization								
BrokerDemandQty/BOInventQty	0.024	4.80	0.13%	1.24	0.078	9.31	0.50%	2.80
UtilizationQty	0.028	5.03	0.23%	1.95	0.089	9.35	0.49%	2.40
TotalDemandQty/BOInventQty	0.028	5.17	0.19%	1.70	0.086	9.36	0.48%	2.47
BOonLoan/BOInventQty	0.028	5.03	0.20%	1.72	0.088	8.95	0.48%	2.32
Special Factors								
IncreasePriceSqueeze	0.026	4.77	0.41%	3.39	0.058	7.94	1.14%	4.29
NegativeSentiment	0.027	4.92	0.21%	1.90	0.082	8.80	0.42%	2.26
PositiveSentiment	0.024	4.55	0.13%	1.19	0.079	7.95	0.39%	2.02

Over our test period, we see impressive performance from several factors in each category (Table 1). The table also reveals that factors generally perform better when the universe is limited to the top and bottom 4% of the Russell 3000. For example, utilization factors generate weekly spreads of at least 0.48% in the 'tailed' universe, compared to 0.23% within the entire Russell 3000 universe.

Focusing on the 'tailed' results, we find that special factors, cost and utilization factors (defined as ratio of demand to supply) have the highest return spreads. Special factors are based on DX's proprietary calculations and combine securities lending data with pricing data to determine positive and negative sentiment for individual securities. The most effective special factor is

IncreasePriceSqueeze, which measures the risk of a rapid jump in price of a heavily shorted security. The performance profile of all utilization signals is similar, which is not surprising, given that all four factors in this category essentially compare the level of demand to the level of supply, using slightly different measurements for demand or supply. Although all the factors in the cost category post impressive weekly spreads, which are all statistically significant, the distribution of factor data in this bucket is also the most skewed out of all the categories we considered.

All the four demand factors yield statistically significant return spreads, with the strongest and weakest factors in this bucket generating weekly spreads of 0.36% and 0.31% respectively. All factors in 'Utilization' category show the strongest performance; which confirms our initial observation that DX data paints a better picture of the securities lending market, as signals constructed on both demand and supply (utilization) generate better performance metrics than those based on demand alone. According to Kaplan et al (2011) and Blocher et al (2010), supply shifts in stock lending are typically driven by changes in investor's marginal cost of lending, which may be related to other factors, including demand for shorting the security; supply of shares affects spot market prices only when borrowing shares is costly. Not surprisingly, we see the weakest performance from the supply category.

3.2 DX Factors vs. Exchange Factors

Many practitioners use short interest (SI) data provided by U.S stock exchanges, which is updated twice a month. In contrast, the DX securities lending database is updated daily. Is there any benefit to using a daily vs. semi-monthly database? We examine the performance of two popular factors built from the two data sources: days-to-cover ratio (DCR) and short interest ratio (SIR). DCR, defined as short interest divided by average daily trading volume, measures the number of days it takes to close a short position and SIR measures short interest as a percentage of shares outstanding. Both factors are broadly used by quantitative managers to track market sentiment. We construct the two factors using the same formula, but different data items in the numerator - DCR (EXCH) and SIR (EXCH) use short interest from exchanges, while DCR (DX) and SIR (DX) use the total demand quantity item from DX. We back tested the four factors on a weekly basis over the Russell 3000 and present this performance, together with the tailed results in Table 2.

Table 2 – Performance Comparison of DCR and SIR Based on DX and Exchanges Data; Universe: Russell 3000; Time Period: July 2006 – October 2011

Strategy	Average IC	IC T-stat	Average Spread	Spread T-stat
DCR(DX)_R3k	0.024	3.97	14.61%	2.78
DCR(EXCH)_R3k	0.023	3.64	12.98%	2.38
DCR(DX)_4% of R3k	0.046	4.38	22.66%	2.38
DCR(EXCH)_4% of R3k	0.039	3.56	15.61%	1.80
SIR(DX)_R3k	0.018	3.28	10.31%	1.79
SIR(EXCH)_R3k	0.017	2.85	9.01%	1.42
SIR(DX)_4% of R3k	0.038	3.96	23.12%	2.57
SIR(EXCH)_4% of R3k	0.035	3.30	21.47%	2.14

In the Russell 3000 universe, factors based on DX data show better performance than those built on exchange data from all aspects – IC, IC T-stat, return spread and spread T-stat. The outperformance is more prominent when the tailed results are used. The average annualized spreads for DCR and SIR based on DX data for the tailed universe were 22.66% and 23.12% respectively, compared to 15.61% (DCR) and 21.47% (SIR) using exchange data. The spread return difference between DCR (DX) and DCR (EXCH) also has a significant t-statistic (2.83). Our results suggest that daily information available from the securities lending market is superior to the semi-monthly short interest data published by U.S exchanges. In addition to timeliness, DX database offers many more data points than are currently provided by the exchanges, as shown in Section 3.1.

4. Multi-Factor Models

We split our entire history into two periods – an in-sample period from July 2006 to March 2009, for factor selection and model creation, and an out-of-sample period from April 2009 to October 2011, for model validation. We selected factors from each category highlighted in Section 3 based on the following criteria: coverage, return spread, turnover, and correlation with other potential candidate factors. All selected factors were equally weighted to calculate a final composite signal.

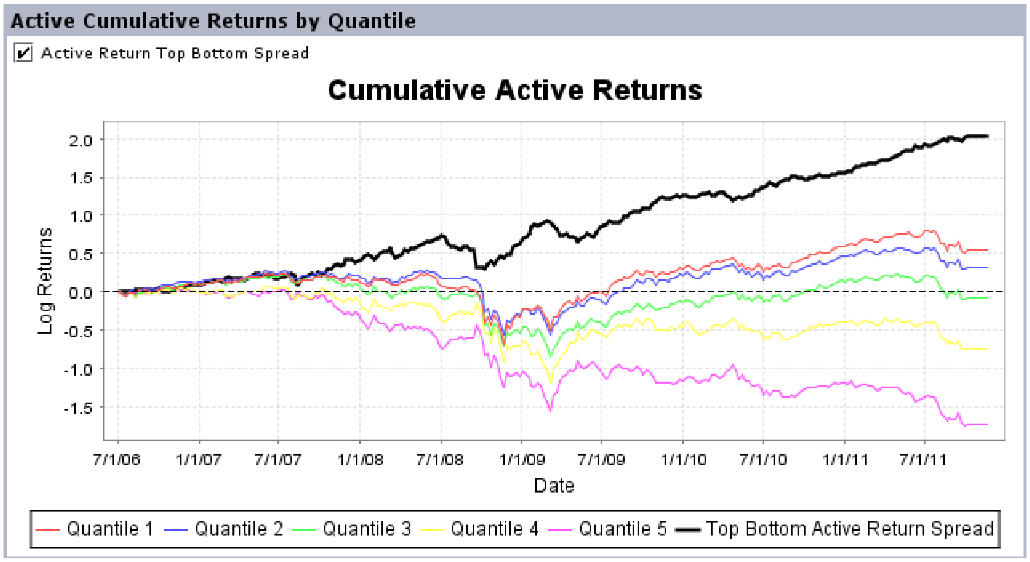
4.1 U.S Model

We present model results in the tailed universe in Table 3. The performance from the preliminary test is quite impressive – the annualized top-bottom return spread is 30.89% for in-sample period, 52.26% for out-of-sample period, and 41.11% for all periods. The T-stats for all return spreads are statistically significant at the 1% level. Figure 5 shows the cumulative return and top-bottom return spread over the entire testing period.

Table 3 – Performance Report for Weekly Backtested Multi-Factor Model; Universe: Top/Bottom 4% of Russell 3000

Testing Period	Average 1 wk IC	1 wk IC T-stat	Ann T/B Spread	Ann Spread T-stat	Ann Spread IR	Quintile Return			
						Q1	Q2	Q4	Q5
In Sample (07/01/06 - 03/31/09)	0.080	5.802	30.9%	2.73	1.19	0.0%	-2.7%	-20.4%	-30.9%
Out of Sample (04/01/09 - 10/15/11)	0.102	9.983	52.3%	7.93	3.45	33.0%	26.2%	6.4%	-19.2%
All Periods (07/01/06 - 10/15/11)	0.091	10.394	41.1%	4.39	1.91	15.7%	10.5%	-7.2%	-25.6%

Figure 5 – Cumulative Returns of Each Quintile for Composite Signal;
Universe: Top/Bottom 4% of Russell 3000; Time Period: July 2006 – October 2011



To determine the profitability of the strategy, we applied a few constraints to our initial strategy. Constraints applied include: adjusting model performance for cost to borrow based on DX supplied data; capping stock forward returns at three cross-sectional standard deviations; and applying a stock price filter with short selling prohibited for securities priced below $5.

Table 4 displays the performance report after a combination of some, or all three conditions are applied. The first three columns indicate if that condition was turned on/off for that back test. The first row shows the base line case that was discussed in Table 3 when no condition was turned on. The last row with only the cost and price filter switched on presents a real world implementation of the model.

Table 4 – Performance Report for the Composite Signal with Adjustments;
Universe: Top/Bottom 4% of Russell 3000; Time Period: July 2006 – October 2011

Adjustment			1 wk IC T-stat	Ann T/B Spread	Ann Spread T-stat	Ann Spread IR	Quintile Return			
Cost	Outliers	Price Filter (<$5)					Q1	Q2	Q4	Q5
No	No	No	10.380	41.29%	4.39	1.91	15.7%	10.5%	-7.2%	-25.6%
No	Yes	No	10.991	44.00%	5.76	2.51	14.0%	10.2%	-15.0%	-30.0%
No	Yes	Yes	9.065	35.89%	4.59	2.00	12.9%	9.1%	-6.1%	-23.0%
Yes	No	No	9.227	30.37%	3.23	1.41	15.7%	10.5%	-7.2%	-14.7%
Yes	Yes	No	9.747	33.55%	4.39	1.91	14.0%	10.2%	-15.0%	-19.6%
Yes	Yes	Yes	8.044	27.15%	3.47	1.51	12.9%	9.1%	-6.1%	-14.3%
Yes	No	Yes	7.881	27.89%	3.09	1.35	13.4%	8.5%	-2.4%	-14.5%

In order to better understand the characteristics of a long/short portfolio, we analyzed the constituents in Q1 and Q5 of the tailed universe (*Table 5*). We find that small cap stocks dominate the short side (Q5), while large and mid-cap dominate the long portfolio (Q1). Interestingly, turnover for all four fractiles appears to be low to moderate. The low turnover, especially for Q5, suggests that transactions costs should not significantly impact the model's return as the securities in this bucket are "sticky".

Table 5 Characteristics of Quintile Portfolios

Characteristics	Q1	Q2	Q4	Q5
Mean Market Cap (in Mil)	9,808	13,047	958	871
Median Market Cap(in Mil)	4,117	4,274	511	453
Average Turnover (%)	9.4%	14.6%	8.5%	4.1%

Additionally, we ran an attribution analysis for the long/short portfolio constructed based on the composite signal using S&P Capital IQ's U.S Fundamental Short Term Risk Model (Table 6). The annualized portfolio return is 34.58% while stock specific return is 40.03%, suggesting that market, industry or style risk factors are not driving the success of this long/short strategy.

Table 6 – Return and Risk Attribution for the U.S Strategy (Composite Signal); Universe: Top/Bottom 4% of Russell 3000; Time Period: July 2006 – September 2011

	Portfolio Exposure	Portfolio Return	Contribution to Portfolio Risk	Realized Percent of Portfolio Risk	Realized Sharpe Ratio
Factor		**-5.44%**	**16.83%**	**53.72%**	**-0.35**
Market	**-0.175**	**0.65%**	**7.05%**	**-5.30%**	**-0.13**
Industry	**0.467**	**0.56%**	**7.43%**	**16.52%**	**0.07**
Style	**1.274**	**-6.65%**	**13.36%**	**42.50%**	**-0.49**
Size	0.517	-2.35%	7.76%	15.21%	-0.29
Price Momentum	-0.092	-2.05%	-2.62%	-1.20%	0.89
Earnings Quality	-0.196	0.01%	-2.35%	-2.22%	0.00
Analyst Expectation	0.266	-0.06%	4.94%	14.63%	-0.01
Volatility	-0.400	-0.73%	7.22%	7.74%	-0.12
Valuation	0.724	0.54%	-2.61%	-4.80%	-0.12
Historical Growth	0.798	-2.83%	9.18%	12.67%	-0.38
Capital Efficiency	-0.344	0.81%	-4.83%	0.46%	0.57
Stock Specific		**40.03%**	**11.47%**	**46.28%**	**2.81**
Grand Total		**34.58%**	**20.37%**	**100.00%**	**1.65**

**** Note: Attribution is based on monthly holding based returns*

4.2 Global Models

We extended our research and model construction methodology to other developed markets, specifically Canada, Europe and Asia. We tested our original U.S model in Canada, Europe, Asia, UK, Europe ex UK, Japan and Asia ex Japan using the respective BMI indices. Testing the U.S model also serves as an "out-of-sample" test as we are using data that was not originally used in factor selection.

Table 7 shows the performance of the U.S Model in these developed markets. We include the U.S model at the top of the table for comparison purposes. The U.S model performs decently in Canada and BMI-Europe, although the performance is not as impressive in Asia. The return spreads are positive and statistically significant in all markets. Furthermore, the robustness across different markets suggests that the success of the signal is not a result of data snooping. The weak performance in Asia compared to other markets may be due to differences in short-selling regulatory policies, which tend to be more restrictive in Asia. Figure 3 also points to the direction that security lending activities are more subdued in Asia than in the other markets we considered.

Table 7 – Performance of the Composite Signal in Global Markets
Universe: Top/Bottom 4% of Country/Region; Time Period: July 2006 – October 2011

Country/Region	Average IC	IC T-Stat	Average T/B Spread	Ann Spread T-stat	Ann Spread IR	Quintile Return Q1	Q2	Q4	Q5
U.S	0.091	10.38	41%	4.39	1.91	15.7%	10.5%	-7.2%	-25.6%
Canada	0.061	8.86	32%	4.97	2.16	13.2%	1.6%	-5.5%	-18.8%
BMI-Dev Europe	0.079	10.37	33%	5.70	2.48	9.3%	4.1%	-15.7%	-23.5%
UK	0.061	6.23	28%	3.77	1.64	13.6%	0.2%	-7.0%	-14.0%
BMI-Dev Europe ex UK	0.090	10.18	33%	5.21	2.27	5.3%	5.5%	-19.8%	-27.4%
BMI-Dev Asia	0.065	8.77	19%	3.40	1.48	-2.3%	-0.6%	-21.4%	-21.0%
Japan	0.059	7.12	16%	3.08	1.34	-5.0%	-4.5%	-17.5%	-21.3%
BMI-Dev Asia ex Japan	0.063	9.12	24%	4.26	1.85	3.8%	1.4%	-9.9%	-20.5%

Having confirmed the efficacy of our initial model in other markets outside the U.S, we followed the same steps we took in building our U.S model to create models for the other markets. Table 8 shows the performance comparison between the U.S model and country/region specific models. The U.S model tested in each market is listed as "US" in parentheses followed by the respective country/region, while the country/region specific model is stated as "Custom". For example, the result of the U.S model tested in Canada is shown in the first row while the custom model built for the Canadian market is shown in the second row. We see improvements in annualized return and annualized IR (custom models vs. the U.S model) in every country/region we tested. The smallest increase in annualized return was in Europe where the top-bottom spread increased by 10% from 32.88% to 36.31%. The improvement in performance in Asia is dramatic, with a 97% and 81% jump in annualized return (U.S: 18.76% vs. Custom: 37.06%) and annualized IR (U.S: 1.48 vs. Custom: 2.68) respectively.

Table 8 – Strategy Comparison – U.S Model vs. Country/Region Specific Model;
Time Period: July 2006 – October 2011

Country/Region	Average IC	IC T-Stat	Average T/B Spread	Ann Spread T-stat	Ann Spread IR	Quintile Return Q1	Q2	Q4	Q5
Canada (US)	0.061	8.86	32.1%	4.97	2.16	13.2%	1.6%	-5.5%	-18.8%
Canada (Custom)	**0.071**	**9.84**	**38.8%**	**5.95**	**2.59**	**14.2%**	**4.2%**	**-5.5%**	**-24.6%**
BMI-Dev Europe (US)	0.079	10.37	32.9%	5.70	2.48	9.3%	4.1%	-15.7%	-23.5%
BMI-Dev Europe (Custom)	**0.081**	**9.18**	**36.3%**	**5.78**	**2.52**	**10.2%**	**4.4%**	**-12.2%**	**-26.2%**
BMI-Dev Asia (US)	0.065	8.77	18.8%	3.40	1.48	-2.3%	-0.6%	-21.4%	-21.0%
BMI-Dev Asia (Custom)	**0.090**	**11.27**	**37.1%**	**6.16**	**2.68**	**1.3%**	**-5.1%**	**-21.3%**	**-35.7%**

5. Blending the Securities Lending Model with S&P CIQ's Stock Selection Models

Next, we confirm if the Securities Lending Model (SLM) can be used to improve the return forecast of existing alpha models. For this test, we blended our U.S stock selection signals (U.S Value Benchmark Model, Growth Benchmark Model, and Quality Model) with SLM. For the combined signals, we ran two sets of tests – for the first set, we assigned a 5% weight to the SLM and a 95% weight to S&P Capital IQ Models (SPCIQ Models); in the second set, we assigned a 10% weight to SLM and 90% weight to SPCIQ Models.

Our analysis starts in July 2006 and ends in October 2011, in line with DX data history, and is based on a weekly rebalancing frequency. Due to the nature of securities lending data, we once again focus on our tailed results (Table 9). The combined models (SPCIQ + SLM) are superior in terms of annualized return spread and 1-month average IC to the stand alone SPCIQ Models in both sets of tests. For example, in the second set of tests, which is highlighted in dark green (SLM weight of 10%), we see a 49% improvement in annual spread (18.0% to 26.8%) for Value model, 63% (18.3% to 29.8%) for Growth Model, and 97% (13.3% to 26.2%) for Quality Model. We also see improvements of 34% (0.91 to 1.22) for Value, 41% (0.89 to 1.26) for Growth, and 68% (0.75 to 1.27) for Quality in annualized information ratios.

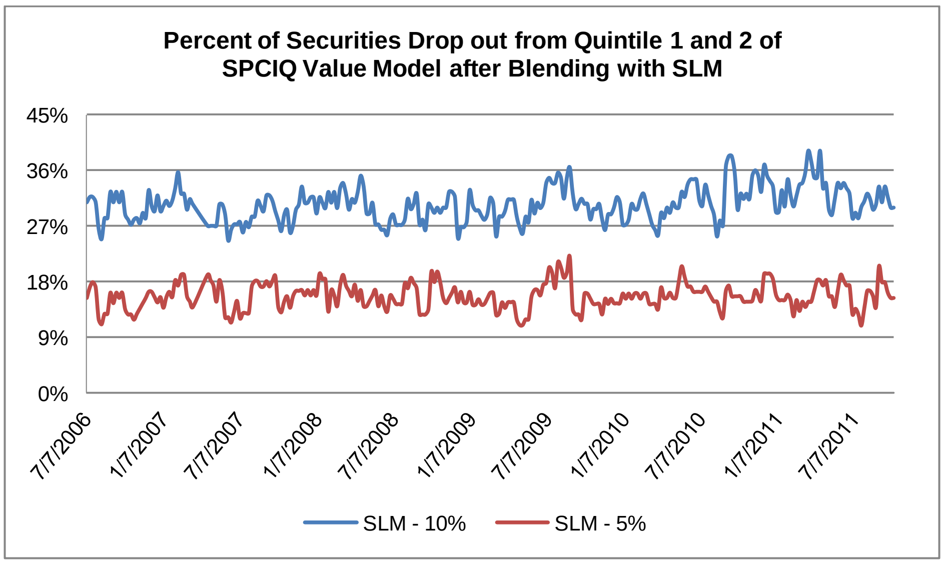
For long only investors, the Securities Lending Model offers opportunities to improve portfolio performance, as we see improvements in both Q1 and Q2 returns when we combine the model with the pure SPCIQ Models. Q1 returns for Value, Quality, and Growth increase by 13% (6.8% to 7.7%), 52% (5.1% to 7.7%), and 27% (4.1% to 5.2%) respectively. Q2 returns are up by 51% (7.4% to 11.2%), 78% (6.4% to 11.4%), and 86% (7.0% to 13.0%) for Value, Quality and Growth models respectively. Long-only investors can also use the Securities Lending Model as a screen to remove or further investigate securities with high negative sentiment from their portfolios.

Table 9 – Strategy Comparison – SPCIQ Models, *SLM, and* SPCIQ Models + *SLM*
Universe: Top/Bottom 4% of Russell 3000; Time Period: July 2006 – October 2011

Strategies	Average IC	IC T-Stat	Average T/B Spread	Ann Spread T-stat	Ann Spread IR	Quintile Return			
						Q1	Q2	Q4	Q5
SLM	0.090	10.35	41.0%	4.38	1.91	17.4%	12.6%	-6.1%	-23.6%
Growth only	0.060	9.03	18.3%	2.04	0.89	4.1%	7.0%	-1.4%	-14.2%
Growth + SLM (5%)	0.072	10.27	24.6%	2.48	1.08	4.6%	11.5%	1.2%	-20.0%
Growth + SLM (10%)	0.077	10.73	29.8%	2.89	1.26	5.2%	13.0%	1.2%	-24.6%
Quality only	0.058	9.14	13.3%	1.73	0.75	5.1%	6.4%	-2.7%	-8.2%
Quality + SLM (5%)	0.069	10.05	20.6%	2.30	1.00	6.2%	9.0%	-0.6%	-14.4%
Quality + SLM (10%)	0.077	10.72	26.2%	2.91	1.27	7.7%	11.4%	-5.9%	-18.5%
Value only	0.067	9.91	18.0%	2.09	0.91	6.8%	7.4%	-9.8%	-11.2%
Value + SLM (5%)	0.076	10.69	22.9%	2.42	1.05	7.3%	13.1%	-9.1%	-16.6%
Value + SML (10%)	0.078	10.71	26.8%	2.81	1.22	7.7%	11.2%	-6.6%	-19.1%

We look more deeply at the return difference between the pure SPCIQ strategy and combination of Value strategy and SLM. For this analysis, we only focus on the long side (Q1 & Q2). Stocks are considered to have dropped out if they are not also in the long portfolio of the blended strategy. Figure 6 shows the percent of securities that drop out from the long portfolio based on the Pure Value Model after we combine the Value model with SML. Our analysis shows that on average about 30% of securities drop out from the Long portfolio (based on SPCIQ Value model) after blending with the securities lending signals (Figure 6: SLM weights 10% - blue line); 16% drops out if SLM signals weights 5% (Figure 6: red line). Blending the SPCIQ Growth and Quality signals with SLM signal shows the similar pattern.

Figure 6 – Percent of Securities Drop out from Quintile 1 Based on SPCIQ Value Model After Blending with Securities Lending Model (SLM); Universe: Top/Bottom 4% of Russell 3000; Time Period: July 2006 – October 2011



As shown in Table 10, the return difference between the long list of combined Model and the pure SPCIQ models are all significant at 95% confidence interval. The hit ratios (defined by positive return difference as percent of total observations) are all above 56%.

Table 10 – Performance Comparison – Pure SPCIQ Models vs. Combined Models Universe: Top/Bottom 4% of Russell 3000; Time Period: July 2006 – October 2011

Blended Signal vs. Pure SPCIQ Signals	% Security Drop-out	T-stat	Hit Ratio
Value + SML (SML=5%) vs. Value	16%	2.78	59%
Value + SML (SML =10%) vs. Value	30%	1.98	56%
Growth + SML (SML =5%) vs. Growth	15%	2.75	58%
Growth + SML (SML =10%) vs. Growth	29%	2.76	59%
Quality + SML (SML =5%) vs. Quality	16%	1.97	56%
Quality + SML (SML =10%) vs. Quality	30%	2.63	60%

6. Removing Securities with Negative Market Sentiment from a Long Only Strategy Using SLM

Long only investors can also use filtering techniques to remove securities with negative market sentiment (measured using SLM), rather than the combination approach adopted in the previous section. For this analysis, we use S&P Capital IQ Value Benchmark Model. Our filtering process is as follows: on each rebalancing date, we rank Russell 3000 companies based on the Value Model into five quintiles. We also independently rank securities based on SLM into twenty quantiles. Among the top Value quintile (Quintile 1) stocks we filter out the securities that are simultaneously in the bottom SLM quantile ("Filtered-out value stocks"). The Filtered-out value stocks are companies that value managers should avoid holding because they rank poorly on SLM. We denote the number of Filtered-out value stocks as N. We denote the securities left in quintile 1 after the Filtered out securities have been removed as "Remaining". Next, we identify N stocks that rank highest among the second value quintile (quintile 2). These securities are denoted as "Replacements" and are used to replace the Filtered-out value stocks. We ensure the Replacements are not in of the bottom SLM quantile either. We then compare the performance of Filtered-out value stocks and Replacements.

The return difference between the Filtered-out list and Replacement or Remaining list are all significant at 95% confidence interval (1.985 and 1.987 respectively); the hit ratios (defined by positive return difference as percent of total observations) for both are around 57% (Table 11).

Table 11 – Performance Comparison – Pure S&P Capital IQ Value Filtered by SLM
Universe: Russell 3000; Time Period: July 2006 – October 2011

	Mean Counts	Weekly Mean Return	Return STDEV	T-stat	Hit Ratio
Value Top Quantile	575	0.16%	0.041		
SLM Bottom Quantile	134	-0.27%	0.050		
Filter-out Names	15	-0.06%	0.046		
Replacement Names	15	0.19%	0.040	(vs. Filter-out) 1.985	(vs. Filter-out) 57%
Remaining Names	560	0.17%	0.041	(vs. Filter-out) 1.987	(vs. Filter-out) 57%

As an overlay strategy, the SLM helps to improve S&P Capital IQ's value strategy by avoiding names that might appear cheap on historical measures/valuation, but have strong negative market sentiment.

7. Conclusion

We demonstrate that the unique data set provided by Data Explorers contains valuable information for an investment process. This data can be used to build a number of univariate factors that generate statistically significant return spreads. Furthermore, the performance profile of a multi-factor model leveraging this data is superior to that of any single factor and generates economically significant returns after applying price filters and accounting for borrowing costs. We believe these results are not a result of data-snooping due to the fact our U.S. model tested relatively well in other developed markets.

Additionally, incorporating our Securities Lending Model can effectively enhance the performance of traditional alpha sources. We find that the integration of securities lending data with our initial stand-alone alpha models achieves encouraging backtest results. While our research conclusions are promising, we would like to note that our study did not formally account for transaction costs and liquidity constraints on model returns. Ultimately, daily securities lending information is a valuable resource from which we can derive non-traditional sources of alpha.

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Appendix A

Data Explorers (www.dataexplorers.com) is a leading provider of securities lending data tracking short selling and institutional fund activity across all global market sectors. DX's content is sourced directly from market participants including prime brokers, custodians, asset managers and hedge funds. It provides a unique data set of more than 3 million intraday transactions across 80 countries, covering US$13 trillion of securities in the lending programs of over 20,000 institutional funds. There are over a hundred data items in Data Explorers database; we have included a list of Data Explorers data items and their definitions below.

Table A.1 Data Items and Definitions

Data Item	Classification	Definition
BO On Loan Quantity	Demand	Quantity of current inventory on loan from Beneficial Owners
Broker Demand Quantity	Demand	Quantity of current securities borrowed by Brokers.
Total Demand Quantity	Demand	Total quantity of borrowed/loaned securities net of double counting
BO On Loan Quantity Decrease	Demand	Change in quantity on loan for existing Beneficial Owners who have decreased quantity of stock on loan
BO On Loan Quantity Increase	Demand	Change in quantity on loan for existing Beneficial Owners who have increased quantity of stock on loan
Broker Demand Quantity Decrease	Demand	Change in quantity of borrowed stock for existing Brokers who have decreased quantity of borrowed
Broker Demand Quantity Increase	Demand	Change in quantity of borrowed stock for existing Brokers who have increased quantity of borrowed stock
Active Available BO Inventory Quantity	Supply	Quantity of shares Floating available for borrowing by removing the Beneficial Owner On Loan Value from the Active Beneficial Owner Inventory Value
Active BO Inventory Quantity	Supply	See above but expressed in shares not value
BO Inventory Quantity Decrease	Supply	Change in quantity of inventory for existing Beneficial Owners who have decreased quantity of inventory
BO Inventory Quantity Increase	Supply	Change in quantity of inventory for existing Beneficial Owners who have increased quantity of inventory
BO Inventory Quantity Add	Supply	Quantity of inventory for existing Beneficial Owners who did not hold stock and now do
BO Inventory Quantity	Supply	Quantity of current inventory available from Beneficial Owners
BO Inventory Quantity Removed	Supply	Quantity of inventory for Beneficial Owners leaving the group
DCBS	Cost	Data Explorers Daily Cost of Borrow Score; a number from 1 to 10 indicating the rebate/fee charged by the Agent Lender (e.g. State Street) based on the 7 day weighted average cost, where 1 is cheapest and 10 is most expensive
SAF	Cost	Simple average fee of stock borrow transactions from Hedge Funds in this security, in bps
SAR	Cost	Simple average rebate of stock borrow transactions from Hedge Funds in this security, in bps
VWAF 1 Day Change	Cost	Change in the 1 day fee average compared to yesterday's 1 day fee average, as a %
VWAF Score 1 Day	Cost	Value weighted average fee for all new trades on the most recent day expressed in undisclosed fee buckets 0-5. 0 the cheapest to borrow and 5 the most expensive

Data Item	Classification	Definition
VWAF 30 Day Change	Cost	Change in the 30 day fee average compared to yesterday's 30 day fee average, as a %
VWAF Score 30 Day	Cost	Value weighted average fee for all new trades on the most recent 30 calendar days expressed in undisclosed fee buckets 0-5. 0 the cheapest to borrow and 5 the most expensive
VWAF All Change	Cost	Change in the average fee for all trades compared to yesterday's average fee for all trades
VWAF Score All	Cost	Value weighted average fee for all open trades expressed in undisclosed fee buckets 0-5. 0 the cheapest to borrow and 5 the most expensive
Utilization	Utilization	Value of assets on loan from Beneficial Owners (BO Value on Loan) divided by the total lendable assets (BOInventory Value), expressed as a percentage.
Active Utilization	Utilization	Demand value as a % of the realistically available supply (BOOn Loan Value/ Active BO Inventory Value)
Active Utilization by Quantity	Utilization	Demand quantity as a % of the realistically available supply (BO On Loan Quantity/ Active BO Inventory Quantity)
DIPS	Others	Compares securities lending data (change in BO inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e. price squeeze). This indicator is based on a scale of 0 to 100 – a DIPS of greater than 20 is considered to be high
DNS	Others	Shows the change in the average BO inventory quantity (longs) in relation to the average total demand quantity (shorts). The scale for this indicator is from 0 to 100. A high DNS generally reflects negative sentiment (an increasing number of shorts relative to longs) while a low number shows relatively less negative sentiment
DPS	Others	Indicator between 0 – 100 that gives higher scores to securities with low and unchanging utilization. These are considered to have higher levels of positive sentiment

Appendix B

One of the challenges of analyzing security lending data is 'Data Cleaning'. Although the most common reason to borrow securities is to cover a short position, investors might borrow for other motivations (e.g., derivative hedge, dividend arbitrage, voting, etc.). It is very important to use a 'clean' data set (with less noise) to interpret the stock lending signals. In order to identify a pattern of change in shares on loan, borrowing cost, and utilization ratio (ratio of demand and supply) around the dividend record dates, we examined the stock lending behavior around those dates across global markets.

Figure B.1 and Figure B.2 show shares on loan as percent of shares outstanding and the utilization ratio for US and BMI developed regions around dividend record dates. There is no obvious pattern observed for Asia around the dividend record date (day 0). For BMI-Europe ex UK, there is a clear pattern of increase in securities lending around the record dates. Shares on loan as percentage of shares outstanding more than doubled around dividend record date – from an average of 1.4% (Ex-Dividend date) to 3.1% (15 days prior to and after the record date). A similar pattern is observed for utilization ratio (from 17 to 32). Figure B.3 shows the cost to borrow score buckets; the cost bucket for Europe Ex UK moves from the 1st bucket (Score = 1 – least shorted) to bucket 3 or bucket 4 around the dividend date. A small spike is also observed for Canada in all figures. Although we see a tiny spike in both shares on loan and utilization for US, the cost to borrow bucket keeps flat all the time. For our data cleaning purpose, we excluded all transactions 10 days prior to and after the dividend record date for Europe ex UK; 1 day prior to and after the dividend record date for Canada. We did not do any adjustment for U.S or Asia.

Figure B.1 Shares on Loan as Percent of Shares Outstanding around Dividend Record Date
Universe: North America and BMI Developed Region
Time Period: July 2006 to October 2011

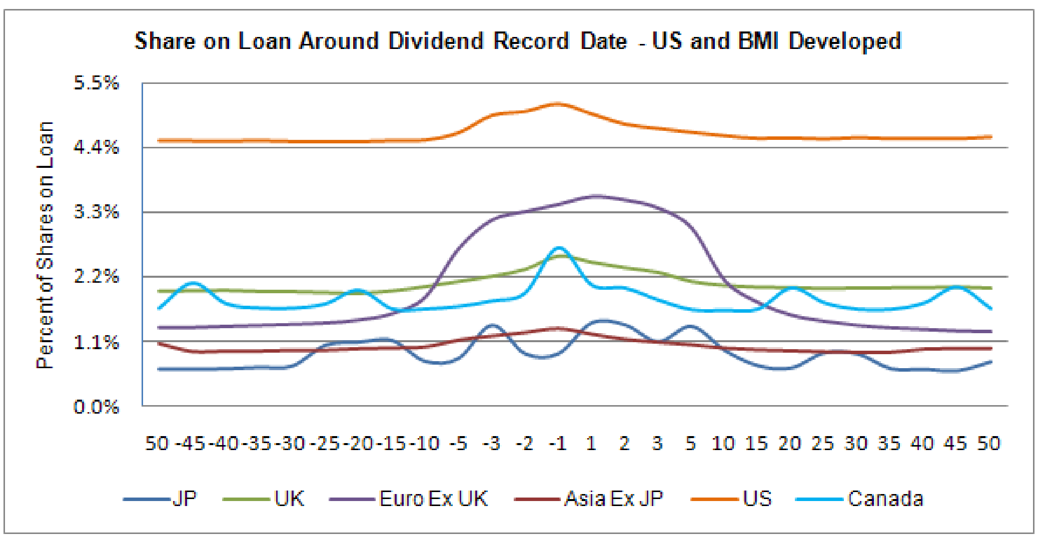


Figure B.2 Utilization Ratio around Dividend Record Date
Universe: North America and BMI Developed Region
Time Period: July 2006 – October 2011

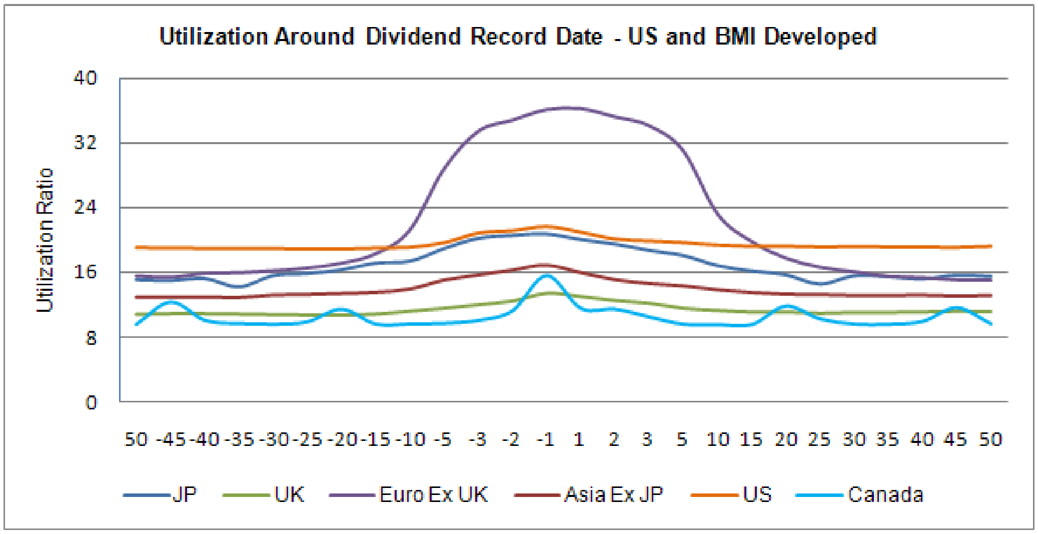
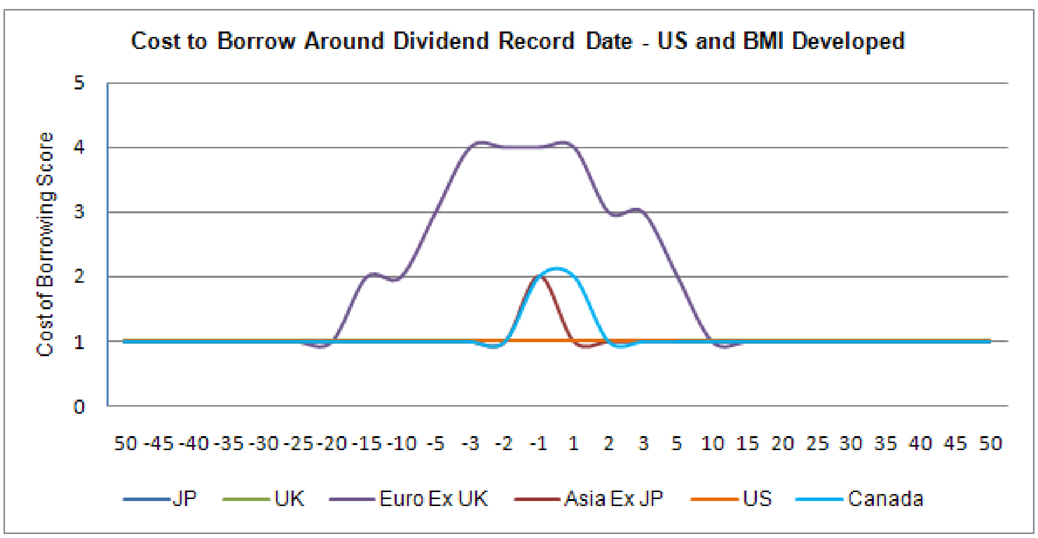


Figure B.3 Cost to Borrow Score Bucket around Dividend Record Date
Universe: North America and BMI Developed Regions
Time Period: July 2006 – October 2011



After our data cleaning, we are left with around 3.5 million observations for the Russell 3000 from July 2006 to October 2011 (there were about 3.6 million initially). The general characteristics across different short interest deciles are shown in Table B.1. As shown in Table B.1, the securities in the highest decile (most heavily shorted) have the highest percent of shares on loan, smallest market cap, and lowest average daily trading volume. The utilization ratio and borrowing cost (defined by average borrowing fees) are higher for the most heavily shorted stocks.

Table B.1 Characteristics across Different Short Interest Buckets; Universe: Russell 3000; Time Period: July 2006 – October 2011

Short Interest	Short Interest Bucket	Shares on Loan as % of Shares Outstanding	Market Cap (Mil - US$)	Average Daily Trading Volume	Utilization	Borrowing Cost (bps)
Lowest	1	0.3%	21,479,463,952	4,386,520	3.39	42.29
	2	0.9%	8,407,955,488	2,295,331	7.01	48.98
	3	1.4%	4,191,141,276	1,481,764	9.82	53.46
	4	2.1%	3,187,170,637	1,358,424	12.92	56.23
	5	2.9%	2,648,414,356	1,317,261	16.58	61.33
	6	3.9%	2,307,868,771	1,274,213	21.08	65.47
	7	5.3%	2,154,770,030	1,305,789	26.21	75.84
	8	7.2%	1,864,073,253	1,283,587	32.97	95.94
	9	10.2%	1,649,870,546	1,434,650	41.72	124.59
Highest	10	17.9%	1,374,488,091	1,518,643	56.36	178.31

In Table B.2, we show some basic lending related information (e.g. % shares on loan, utilization, and borrowing cost) for each sector in Russell 3000 universe. Consumer Discretionary has the highest shares on loan and utilization ratio, while Health Care shows the highest borrowing cost.

Table B.2 Securities Lending across GICS Sectors; Universe: Russell 3000; Time Period: July 2006 – October 2011

Sector	Number of Observations	Shares on Loan as % of Shares Outstanding	Market Cap (Mil - US$)	Average Daily Trading Volume	Utilization	Borrowing Cost (bps)
Consumer Discretionary	548,971	7.0%	3,340,086,031	1,795,619	27.54	85.58
Information Technology	583,103	5.1%	5,148,512,406	2,435,100	20.77	64.24
Financials	722,221	4.8%	4,089,458,256	1,703,160	23.11	89.92
Energy	212,379	4.9%	8,353,723,226	2,187,646	23.83	96.32
Industrials	505,178	5.1%	3,955,239,182	1,118,674	20.66	67.88
Utilities	112,999	3.4%	5,674,559,618	1,294,838	15.46	37.87
Materials	171,221	3.9%	4,074,151,301	1,712,188	18.09	63.30
Health Care	444,275	5.4%	4,692,890,265	1,308,554	25.38	100.80
Consumer Staples	150,125	4.5%	11,612,645,688	2,016,894	21.31	90.07
Telecommunication Services	49,078	4.3%	10,549,531,870	3,908,551	21.31	63.96

Appendix C

Classification	Factor	Definition	Rationale
Demand	Days to Cover Ratio (DCR)	Quantity on loan (securities lending) from lenders or/and brokers / Average daily trading volume	Days to cover ratio; it tells approximately how many days it will take short-sellers to cover their positions. The higher the ratio, the longer it will take to buy back the borrowed shares. It is indicative of the potential of a short squeeze. Short interest ratio measures percent of shares on loan and serves as market sentiment indicator. All factors in this category designed to capture market sentiment and measure how difficult to cover a short position.
	Short Interest Ratio (SIR)	Quantity on loan (securities lending) from lenders or/and brokers / Shares outstanding	
	Change of DCR or SIR	1 Day or 3 Day change of DCR or SIR	
Supply	(Active/Available) Shares for Borrow as Percent of Average Daily Trading Volume	Supply for securities lending comes from long holdings / Average daily trading volume	Measures the amount of securities made available for lending. It shows how difficult to borrow a stock; therefore, it is one of key risk control measures.
	Percent of (Active/Available) Shares for Borrow	Supply for securities lending comes from long holdings / Shares outstanding	
	Change of Percent of Shares available for Borrow	1 Day or 3 Day change of shares for borrow as percent of average daily trading volume	
	Percent of (Active/Available) Shares for Borrow	1 Day or 3 Day change of percent of shares available for borrow	
Cost	Cost t o Borrow Score	Data Explorers Daily Cost of Borrow Score; a number from 1 to 10 indicating the rebate/fee charged by the Agent Lender based on the 7 day weighted average cost, where 1 is cheapest and 10 is most expensive	Borrowing cost is one of the key constraints for short sale. It indicates how difficult to borrow a particular stock. Generally, it is easy and cheap to borrow most large cap stocks, but it can be difficult to borrow stocks that are small, have low institutional ownership, or are in high demand for borrowing. It is one of key drivers of shift in the supply and demand curve.
	VWAF Score	Value weighted average fee expressed in undisclosed fee buckets 0-5. 0 the cheapest to borrow and 5 the most expensive	
	Simple Average Fee	Simple average fee of stock borrow transactions from Hedge Funds in this security	
	Simple Average Rebate	Simple average rebate of stock borrow transactions from Hedge Funds in this security	

Classification	Factor	Definition	Rationale
Utilization	Demand / Supply Change of Utilization	Demand (Beneficial Owner On Loan) as percent of (available) supply (Beneficial Owner Inventory) Change of demand to supply ratio	Key measure of risk - highly utilized stocks are more subject to short squeeze risk due to very limited supply of the lendable stocks.
Special Factors	Negative Sentiment (DNS) Positive Sentiment (DPS)	Sum of the moving average of utilization (a DX measure of supply vs. demand in the securities lending market) and the change in utilization. Ratio of the average loan quantity (shorts) relative to average inventory quantity (longs) for the security.	The indicators are based on a relative scale (normalized) from 0 to 100. A relatively high DNS generally reflects negative sentiment (an increasing amount of shorts relative to longs) while a low number shows relatively less negative sentiment. DPS is exactly opposite.

Appendix D

Factor Category	Formulation
Demand	
DCR(TDQ)	Ratio of Total quantity of loaned securities to Monthly average daily trading volume
DCR(BOOL)	Ratio of Quantity of current inventory on loan from Beneficial Owners to Monthly average daily trading volume
SIRatio(BOOL)	Ratio of Quantity of current inventory on loan from Beneficial Owners to Shares outstanding
Supply	
ShrAvailabletoBorrow/SOS	Shares available to borrow (defined by difference of supply and demand) as percent of Shares outstanding
ActiveAvailableBOInventQty/SOS	Active Long Inventory Supply Quantity as percent of Shares outstanding
ShrAvailabletoBorrow/AMTV	Ratio of Shares available to borrow (defined by difference of supply and demand) to Average daily trading volume
ActiveAvailableBOInventQty/AMTV	Ratio of Active Long Inventory Supply Quantity to Average daily trading volume
Cost	
CosttoBorScore	Data Explorers Daily Cost of Borrow Score; a number from 1 to 10 indicating the rebate/fee charged by the Agent Lender based on the 7 day weighted average cost, where 1 is cheapest and 10 is most expensive
vwafallScore	Value weighted average fee score for all open trades
vwaf60DScore	Value weighted average fee score based on the last 60 trading days
vwaf30DScore	Value weighted average fee score based on the last 30 trading days
Utilization	
BrokerDemandQty/BOInventQty	Quantity of current securities borrowed by Brokers as percent of Quantity of current inventory available from Beneficial Owners
UtilizationQty	Ratio of Beneficial Owner On Loan Quantity to Beneficial Owner Inventory Quantity
TotalDemandQty/BOInventQty	Total quantity of loaned securities as percent of Quantity of current inventory available from Beneficial Owners
BOonLoan/BOInventQty	Ratio of Quantity of current inventory on loan from Beneficial Owners to Quantity of current inventory available from Beneficial Owners

Special Factors	
IncreasePriceSqueeze	Compares securities lending data (change in inventory quantity and loans) to cash market data (average trading volume and price) to determine the risk of rapid increase in price
NegativeSentiment	The change in the average BO inventory quantity (longs) in relation to the average total demand quantity (shorts)
PositiveSentiment	Average loan quantity (shorts) relative to average inventory quantity (longs)

Our Recent Research

February 2012: Papers that caught our Interest: Interesting & Influential
When we get a new investment idea, two questions immediately come to mind. What literature already exists around this topic? What were the findings? As good research practice, we seek to identify how we can adapt and fine tune our ideas to overcome some of the limitations of past studies, and whether we can use new data sources to augment/validate our thoughts. In short, how can we convert our idea into something that can add value?

January 2012: S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011
In this report, we review the performance of S&P CIQ's four U.S stock selection models in 2011. These models were launched in January 2011, and this analysis will assess the underlying drivers of each model's performance over the last 12 months.

January 2012: Intelligent Estimates
As residual stakeholders, equity investors place enormous importance on a company's earnings. Analysts regularly forecast companies' future earnings. The prospects for a company's future earnings then become the basis for the price an investor will pay for a company's shares. Market participants follow sell side analysts' forecasts closely, identifying those analysts that demonstrate forecasting prowess and track those analysts' forecasts going forward.

December 2011: Factor Insight – Residual Reversal
Many investors employ price reversal strategies (strategies that buy "losers" and sell "winners" based on short-term price changes) in their stock selection decisions. One popular reversal strategy is constructed as the change in 1-month stock price over the most recent month. This report compares the performance of this factor to a "residual reversal" signal proposed by Blitz, Huij, Lansdorp and Verbeek in their 2011 paper, "Short-Term Residual Reversal".

November 2011: Research Brief: Return Correlation and Dispersion – All or Nothing

October 2011: The Banking Industry
Investors can improve model and portfolio risk adjusted returns using various approaches, including incorporating new alpha signals in an existing investment process. In this research piece, we build on our earlier work (See "Is your Bank Under Stress? Introducing our Dynamic Bank Model", November 2010), to determine if bank specific data provided by financial institutions regulatory bodies (FFIEC standardized data), can yield alpha signals orthogonal to those found in most stock selection models.

September 2011: Methods in Dynamic Weighting
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.

September 2011: Research Brief: Return Correlation and Dispersion – Tough Times for Active Managers

July 2011: Research Briefs – A Topical Digest of Investment Strategy Insights
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? In this report we highlight several classes of questions that investors are routinely interested in and share our thoughts on these topics.

June 2011: A 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 S&P Capital IQ's quantitative research begins a more thorough examination 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.

May 2011: Introducing S&P Capital IQ's Global Fundamental Equity Risk Models
Global investors invest in assets across multiple countries. Building on the success of S&P Capital IQ's release of our U.S. Fundamental Equity Risk models we use similar building blocks viz. the best of breed point-in-time S&P Capital IQ data, state of the art Alphaworks alpha factor library, GICS global industry classification system and an open and robust risk estimation methodology to construct the S&P Capital IQ Global Fundamental Equity Risk Model.

May 2011: Topical Papers That Caught Our Interest

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

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 S&P 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 S&P 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

November 2010: Is your Bank Under Stress? Introducing our Dynamic Bank Model

October 2010: Getting the Most from Point-in-Time Data

October 2010: Another Brick in the Wall: The Historic Failure of Price Momentum

July 2010: Introducing S&P Capital IQ's Fundamental US Equity Risk Model