Short Squeeze model

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MARKIT RESEARCH SIGNALS

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A systematic signal to identify short squeeze events

Extending our series on short squeeze research, we introduce the Short Squeeze model to systematically score stocks based on their potential for a short squeeze event. Using Markit's short loan transaction data, our model incorporates capital constraint indicators, which identify names where short sellers have increased potential to cover positions, and events, identifying catalysts for short squeezes. The model can be used to improve alpha forecasts based on short interest measures, and can be used to supplement existing models, which we demonstrate by measuring the improvement of our US models in a short squeeze model overlay strategy.

- Short squeeze candidates identified by the model within our highly shorted universe had a 78% greater likelihood of squeezing during the model development period
- Stocks with the highest probability to squeeze outperform the universe for open-to-close returns, with an additional 7 bps of return on average versus the universe and 12 bps versus names least likely to squeeze. Positive returns extend out to 1-month holding periods with 44 bps and 103 bps of additional alpha, respectively
- Using the model as an overlay with other short sentiment strategies to close out positions which are at risk of a squeeze in the short portfolios, we report improved performance of 15 bps on average per month

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Introduction

We recently opened up a series of publications surrounding the phenomenon of short squeezes, beginning with an academic approach introducing the concept of short squeezes, the complications surrounding their identification and attribution analysis around the set of names identified for our base universe (The Long and Short of Short Squeezes, November 2013).

Given the loose use of the term "short squeeze" in the media and the debatable prevalence of the phenomenon, we outlined a systematic identification process for squeezes.

The conditions that we require for a squeeze include a sudden spike in price (3 standard deviation move versus prior 60 trading days over 1-3 days), followed by a decrease in shares on loan (over 5 consecutive days), for names with insufficient supply of shares and high borrowing costs in the securities lending market bottom quintile of demand supply ratio and implied loan rate). We are also careful to filter out dividend arbitrage activity (see the Appendix for a detailed definition).

Our first publication served as the base for our next steps to combine the underlying short loan transaction signals with our proprietary factor data and news events to measure short squeeze risk. In our second publication, we took a closer look at the first of these interaction terms with specific focus on transaction level data sourced from our Securities Finance data (Innovations in Short Loan Transaction Analysis, August 2014). Our Securities Finance daily feed provides an advantage in estimating short squeeze expectations when compared to traditional short interest data provided by the exchanges on a bi-monthly basis.

We establish that underlying every short sale is a securities lending transaction captured by our database. With this transaction-level detail, we can approximate the money-ness of each short sale, i.e., whether it is in- or out-of-the-money, an issue confronting short sellers in deciding to maintain or unwind their positions and the urgency of that decision.

We examined our transaction-level shorting flow data to produce five unique indicators that can help identify potential short squeezes – Profit and Loss Impact, Out-of-the-money Percent, Transact Duration, Max Quantity Bins and Out-of-the-money Days-to-cover. We reported detailed analytics on these new signals providing visualisation to better understand their underlying meaning and characteristics, along with descriptions of their efficacy in short squeeze identification.

Our final study in the short squeeze series focuses on the application of these factors in a model to score stocks based on short squeeze potential. In addition, we incorporate events related to short squeezes, such as earnings or other corporate announcements, with the ultimate goal of constructing a systematic signal using the full extent of our research.

In the remainder of this report we introduce our Short Squeeze model, which incorporates insights from the transaction-level capital constraint factors and event indicators that demonstrate its use in predicting squeezes as well as alpha generation. We start with an overview of the datasets used and the model construction. Next, we discuss backtest results of the model, including short squeeze prediction frequencies and model returns. We also present results of strategies using the model as an overlay to short interest factors and our US style models. We round out the report with examples of stocks where the model successfully predicted a short squeeze event.

Data and methodology

We begin with a description of the background data and underlying methodology. First, we review our Securities Finance data, which provides the underpinnings for the transaction-level indicators. Next we introduce RavenPack data, which is used to classify news events and is newly introduced in our Short Squeeze model. Lastly, we describe the construction of the model.

Markit's Securities Finance data

Markit's Securities Finance data provides a timely, detailed look at the short interest market. Names in high demand, a proxy for highly shorted, and those with a high cost to borrow tend to underperform the market. At the same time, highly utilized names are at risk of short squeeze. Within the highly utilized set of stocks, we aimed to identify those at risk of a squeeze to improve accuracy of short interest signals and provide deeper insight into short positions, the principles behind our detailed definition of a short squeeze.

We hypothesize that short squeezes are more likely to occur for stocks in which short sellers are experiencing capital constraints. In other words, they are losing or are at risk of losing money on their positions. We turn to our Securities Finance transaction data from both lenders and borrowers (net of double counting) to provide insight into the underlying stock lending transactions. The details we look to uncover include the duration of the open position, the price at which the position was entered, the quantity of shares on loan that are losing money and the average break-even price.

Profit and loss (PnL) is a key parameter in the construction of several pertinent factors. Briefly, to compute PnL, we begin by determining the start date of the short sale to set the initial price based on

the date that the initial short was placed with the broker. The aggregate PnL for a stock is the weighted sum of all PnLs for each short position, using the number of shares on loan.

RavenPack data

RavenPack produces a structured sentiment scoring system based on unstructured news articles from major media providers and newswires. Over 30,000 listed stocks are covered, spanning the Americas, Europe and Asia, and the data provides realtime statistical summaries of the amount and content of text news. In this model, we use the RavenPack News Analytics version 3.0, which sources news articles from Dow Jones Newswires, online publications and blogs. The news data provides information about companies cited in each news article, descriptions of the type of news event, and sentiment and relevance scores for each event. We leverage both individual articles as well as aggregated sentiment values in this model.

While Ravenpack produces sentiment analysis on a wide range of news stories, our research has narrowed the focus to four specific event types:

1. M&A – we capture confirmed and expected M&A events as well as rumours about M&A activity that can affect short sellers
2. Earnings sentiment – these articles identify positive sentiment related to earnings releases and forecasts
3. Trading activity – news articles describing order imbalances with a positive sentiment, index rebalances and stock buybacks are captured in this category
4. Other positive news events such as patent approvals and completed debt restructuring

We look for events that fall into these four categories and which also have high relevance and sentiment scores. In the next section, we describe how this data is implemented into the model.

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Model description

We introduce the following set of capital constraint indicators constructed from transaction-level data to assist in identifying potential short squeezes:

Out-of-the-money Percent (OTM%) – the sum of shares for short positions that are experiencing losses based on their PnL divided by the total shorted quantity. We expect names with a high percent of short sellers out-of-the-money to be at risk of a short squeeze.

Out-of-the-money Percent - 20-day maximum – the maximum OTM% over the prior 20 trading days. The 20-day maximum value removes the effect of short term price movement and identifies the "worst case" scenario for short sellers.

Short Position Profit Concentration – the distribution of a stock's short loan position profit/loss based on a predefined set of bins. We expect names with a high concentration of short sellers near the break-even point to be at higher risk of a short squeeze.

These capital constraint factors identify the conditions for a short squeeze. We also find certain events increase the probability of a short squeeze:

Earnings announcement events – our research finds that short squeezes happen more frequently around earnings announcement dates. We use this as an indicator to increase the probability of a squeeze five weekdays prior to an earnings announcement and the three weekdays following the announcement.

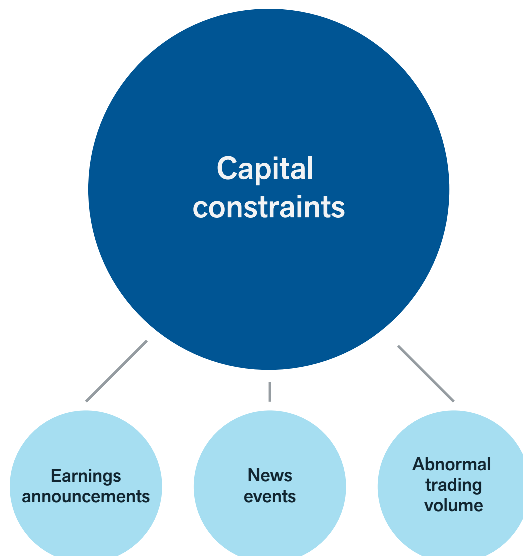
Positive news events – we use RavenPack news events to identify potential positive news events that can trigger a short squeeze. Event types include merger and acquisition, earnings, trading and other positive events, as described in the methodology section.

Abnormal trading volume – we find cases where abnormal trading volume levels paired with positive price movement are indicative of a positive event known to market participants which can trigger a short squeeze.

Finally, our Short Squeeze modelincorporates the capital constraint and event indicators into a final score (see figure 1). The capital constraint indicators identify names with potential for a short squeeze and are ranked from 1 to 100 and then averaged on an equal-weight basis into a composite rank.

The event indicators identify the catalysts for the short squeeze and improve the composite rank based on event type. Positive news events are rewarded with an increase of 20 ranks since we have found the highest connection between these events and future short squeezes. Earnings announcements and abnormal trading volume events increase the composite by 10 ranks. When multiple events occur at the same time, the maximum score increase is 30 ranks.

Figure 1: Short Squeeze model exhibit



In the following section, we review model performance. Recall that our coverage universe consists of highly shorted companies from Markit's US Total Cap universe, representing 98% of cumulative market cap, or 3,000+ stocks. Our in-sample period spans January 2011 to March 2014 and results in 346,537 observations. We then filter this universe based on our systematic definition to arrive at our set of 3,260 short squeezes.

We remark that short squeezes do not occur as frequently as commonly cited and results in a minimal set of outcomes, approximately 251 events per quarter on average.

Results

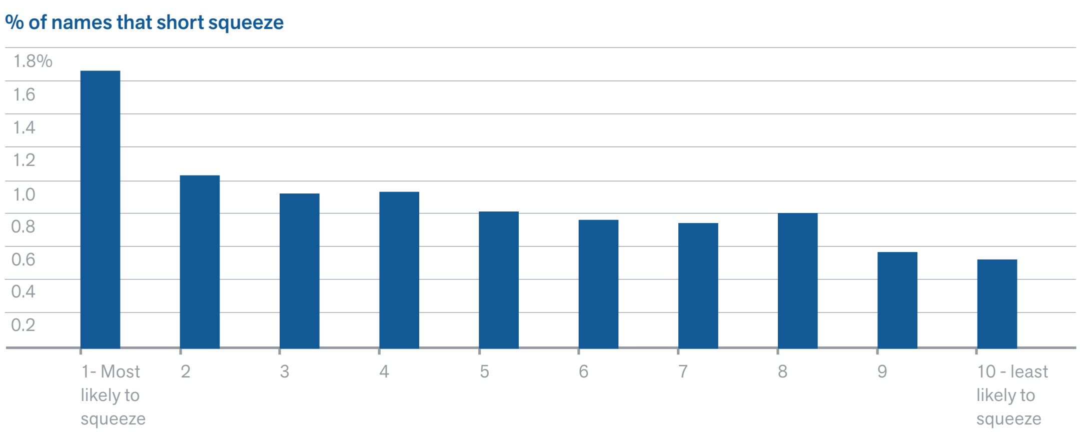
Our model performance review covers two aspects of the results: short squeeze prediction and alpha generation. We begin with an analysis of the likelihood that model scores predict short squeezes.

We analyse decile groups with decile 1 (D1) representing the names most likely to squeeze and decile 10 (D10) those least likely. Figure 2 displays the percent of names that experienced a short squeeze on average in each decile.

First, we report our results for our in-sample period of January 2011 – March 2014. We find that squeezes occur on average 0.94% of the time on a daily basis in our highly shorted universe.

Based on our model scores, we find that squeezes occurred 1.67% of the time in D1. In other words, for names most likely to squeeze, there is a 78% greater likelihood. Furthermore, the occurrences decrease in general across deciles with D10, representing names least likely to squeeze, exhibiting the lowest occurrence.

Figure 2: Percent of names that short squeeze, January 2011 – March 2014



With squeeze prediction established, we consider application of our model in terms of its alpha generating capabilities. Our premise is that stocks which are identified as the most likely to squeeze are expected to outperform given the higher propensity for their prices to increase as short sellers cover their positions. We analyse open-to-close, 1-week, 2-week and 1-month subsequent spread returns based on model scores for the coverage universe over the analysis period (see table 1). We report the excess return of D1 short squeeze stocks versus the highly shorted universe along with the spread returns of D1 (highest probability) versus D10 (lowest probability) stocks. For reference, we also include the percent of squeezes that occurred over the respective holding periods for D1 and the universe.

Our results show that D1 stocks outperform the universe over multiple holding periods. For open-to-close returns, D1 provides an additional 7 bps of return on average versus the universe and 12 bps versus D10. Positive returns extend out to longer holding periods where D1 outperforms the universe (D10) by 19 bps (30 bps) for 2-week returns and 44 bps (103 bps) for 1-month returns.

Further robustness checks over the respective holding periods confirm that stocks which the model predicts to squeeze do squeeze more frequently than the highly shorted universe. For open-to-close periods, the frequency of squeezes in D1 is 1.67% versus 0.94% for the universe. At the 1-month horizon, the spread between frequencies expands from 20.27% for D1 versus 17.20% for the universe.

Table 1: Short Squeeze model performance, January 2011 – March 2014

Holding period	D1 excess return	D1 vs. D10 return spread	Squeeze % for D1	Squeeze % for universe
Open/close	0.08%	0.13%	1.66%	0.94%
1 week	0.05%	0.02%	5.78%	4.48%
2 week	0.21%	0.32%	10.50%	8.48%
1 month	0.54%	1.12%	20.40%	17.20%

With in-sample model efficacy established, we turn next to out-of-sample results from April 2014 through March 2015 (see table 2). The results are consistent with the in-sample results. We again see higher squeeze frequency for the model D1 names than we do for the overall universe over multiple holding periods.

Also, we find positive excess returns associated with the model in the out-of-sample period. In fact, the returns are of greater magnitude relative to the in-sample period results. For example, we find impressive D1 excess returns of 1.20% on average for monthly overlapping results.

Table 2: Short Squeeze model out-of-sample performance, April 2014 – March 2015

Holding period	D1 excess return	D1 vs. D10 return spread	Squeeze % for D1	Squeeze % for universe
Open/close	0.12%	0.20%	1.15%	0.90%
1 week	0.32%	0.86%	5.20%	4.38%
2 week	0.52%	1.43%	9.78%	8.50%
1 month	1.20%	3.02%	19.12%	16.96%

We further illustrate the favourable model performance with accompanying time series graphs covering the full sample period. Figure 3 displays the D1 open-to-close returns relative to the universe over the analysis period. We also include the cumulative growth of $1 to demonstrate the persistence in outperformance cumulating to 150% growth.

Lastly, we take a closer look at D1 monthly returns (overlapping periods) versus the universe (see figure 4). The image shows consistency in outperformance with positive returns in 61% of observations.

Figure 3: Short Squeeze model open-to-close performance, January 2011 – March 2015

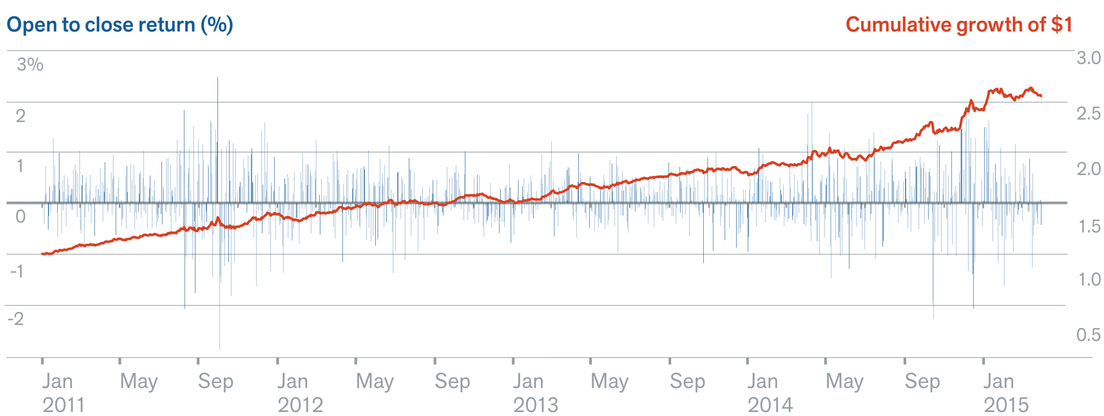
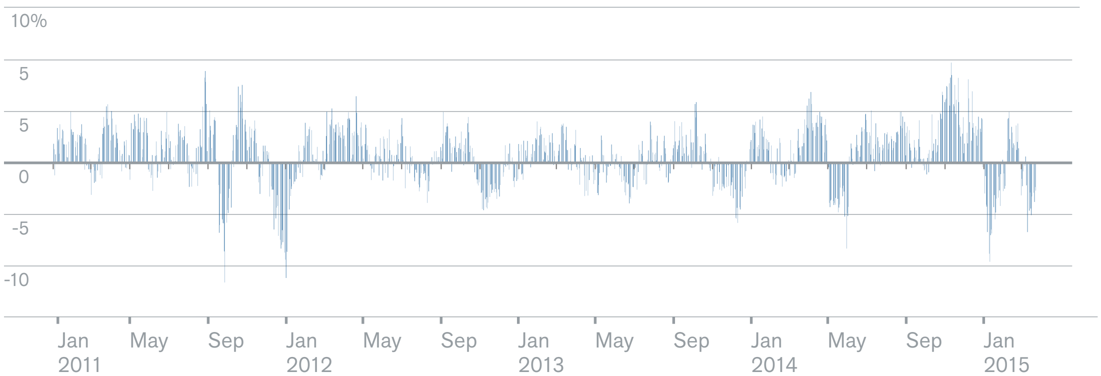


Figure 4: Short Squeeze model 1-month (overlapping periods) performance, January 2011 – March 2015



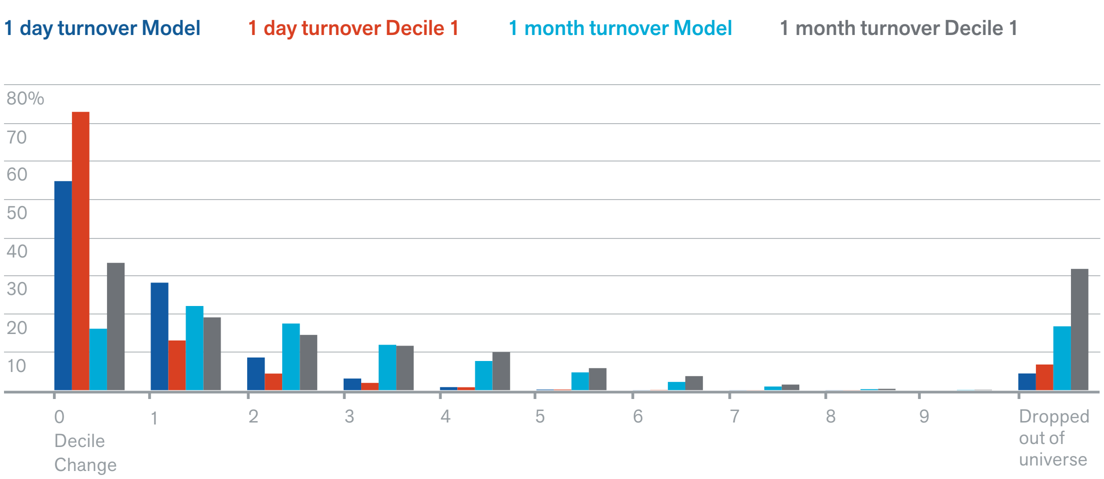
Finally, we detail the turnover statistics of the model ranks (see figure 5). As may be expected, when incorporating event measures that are short term in nature, the turnover of the model can be higher than our typical models. We study turnover by measuring the percent of stocks which move X number of deciles from one period to the next. We study both the decile changes for the model and for D1 specifically, and we look at one-day and one-month time horizons.

Results show that the model ranks do indeed change frequently. For the model overall, we expect 55% of names to remain in the same decile the next day, and 28% to change one decile.

As we extend the time period to one month, we find the decile changes to be quite higher, with only 16% of names remaining in the same decile.

Focusing on the top decile only, we find the model is more stable. For D1, 73% of names remain in D1 the following day, with 33% of the names remaining in D1 one month later. In addition, we find that more D1 names exit the highly shorted universe than over the model as a whole (7% versus 3% daily). These turnover levels suggest the model may be best used in conjunction with other signals, and we detail an overlay strategy in the following section.

Figure 5: Short Squeeze model turnover, January 2011 – March 2014



Short Squeeze model application

Next, we turn to using the Short Squeeze model in combination with other factors and models.

We will first focus on factors related to short interest and securities lending, and then we will investigate how this model can supplement our existing US models. To implement the Short Squeeze model as an overlay to an existing strategy, we form our long/short portfolios based on factor/model ranks at the end of each month. The strategy is to go long on the names in D1 and short the names in D10 with a one-month time horizon. We then use the Short Squeeze model to close out positions in our short portfolio which are at risk of a short squeeze. More specifically, if a stock in D10 is ranked at the top of the Short Squeeze model on the date of portfolio formation, we will not include the stock in our short portfolio. In addition, as we move forward throughout the month, if a stock moves into the top decile of the Short Squeeze model, we will close that short position at the close of the day following the signal. We compare factor/model results for the model both with and without adjustment for short squeeze using both mean return and information ratio.

We find that applying the Short Squeeze model as an overlay to single factors based on short interest data or our securities lending data improves the performance of the factors on both mean return and information ratio. The Short Interest Ratio (also called Days to Cover) which measures the ratio of shares shorted to trading volume sees an improvement on average return spread from 0% to 0.189% monthly (see table 3). The short interest position (shares shorted to shares outstanding) also improves from 0.352% to 0.447%, while the information ratio increases from 0.109 to 0.169. Using our Securities Finance data on shares on loan to shares outstanding, we again see an improvement from 0.304% to 0.456% with a healthy increase in information ratio. In addition, we display the percent of stocks in D10 for each factor which our model indicates to close the position. Perhaps not surprisingly, the percent is fairly high for these factors as they are focused on the stocks which are most highly shorted. For example, 22% of D10 stocks were closed out during the month on average for the Short Interest Ratio factor.

Table 3: Factor and Short Squeeze model overlay performance, January 2011 – March 2014

	D1 - D10		D1 - D10 - SSQ adjusted		Improvement		% D10 closed
Factor	**Average**	**IR**	**Average**	**IR**	**Average**	**IR**	
Short Interest Ratio (exchange data)	0.00%	0.000	0.19%	0.081	0.19%	0.082	22%
Short Interest Position (exchange data)	0.35%	0.109	0.45%	0.169	0.10%	0.060	33%
Shares on loan to shares outstanding	0.30%	0.106	0.46%	0.188	0.15%	0.082	32%

Next we investigate the impact of the Short Squeeze overlay on our US models (see table 4). We again see positive results, although in general the impact is not as strong as we saw when applied to the short interest factors. This may be expected, as we also see a lower percentage of stocks that fall in D10 and are also flagged as a squeeze risk, on average. Overall, all models see modest improvement in both mean return spread and information ratio except the Price Momentum model, which sees a slight deterioration in performance.

The Relative Value model improves the most as measured by both the mean return and information ratio. The Value Momentum Analyst 2 model improves by 0.67 on the information ratio, revealing a large decrease in risk.

Table 4: US style model and Short Squeeze model overlay performance, January 2011 – March 2014

	D1 - D10		D1 - D10 - SSQ adjusted		Improvement		% D10 closed
Model	**Average**	**IR**	**Average**	**IR**	**Average**	**IR**	
Deep Value model	0.57%	0.180	0.57%	0.205	0.00%	0.025	14%
Earnings Momentum model	1.23%	0.701	1.25%	0.714	0.01%	0.013	9%
Price Momentum model	0.63%	0.248	0.62%	0.245	-0.02%	-0.002	13%
Relative Value model	0.84%	0.266	0.91%	0.339	0.07%	0.073	15%
Historical Growth model	-0.14%	-0.081	-0.10%	-0.054	0.04%	0.027	38%
Value Momentum Analyst 2 model	1.05%	0.401	1.05%	0.468	0.00%	0.067	16%

Model rank examples

To further illustrate the model in action, we review the model ranks and returns for Netflix around their Q1 2013 earnings announcement. In the days preceding the earnings announcement on January 24th 2013, short sellers in Netflix were holding positions very close to the breakeven point of profitability.

The day before the earnings announcement, nearly all short sellers were losing money on their positions, and there was a high concentration of short sellers losing 0-5% on their positions (see figure 6).

The Short Squeeze model rank moved between 10 and 30 in the two weeks before the earnings announcement, and jumped to a rank of 1 on January 23rd. Netflix beat their earnings estimates on January 24th, leading to short covering and a return of 64.2% over the following two days (see figure 7).

Figure 6: Netflix realized PnL percent, January 23rd 2013

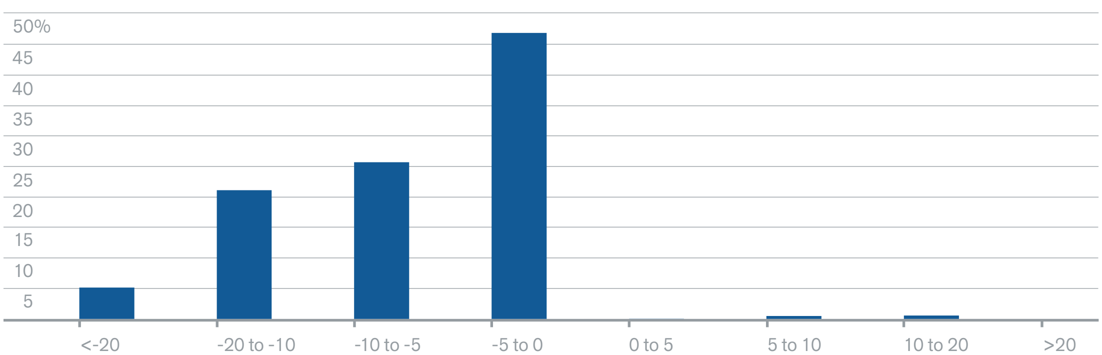
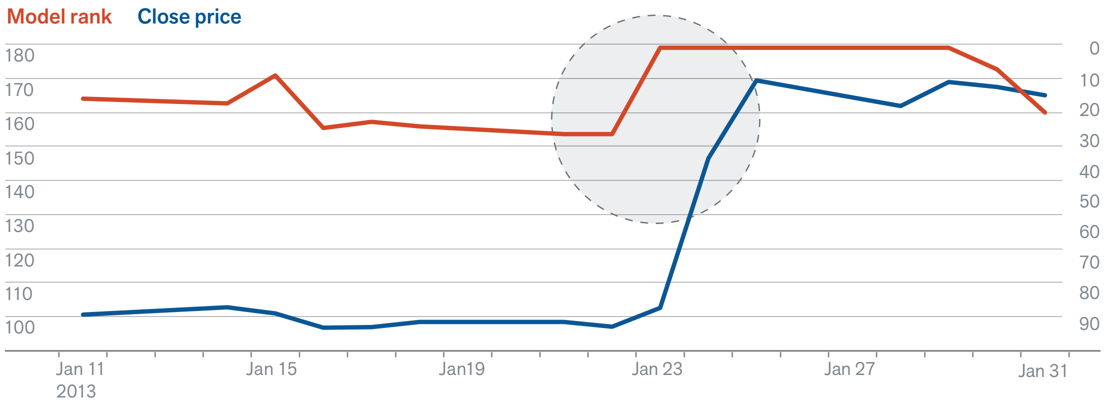


Figure 7: Netflix Short Squeeze model ranks and prices, January 11th 2013 – Jan 31st 2013



To further illustrate the model output, in table 5 we present a sample of names scoring at the top of the model as of the close of April 29th 2015.

Table 5: Short Squeeze model percentile ranks, April 29th 2015

Ticker	Name	Rank
LOGI	LOGITECH INTL S A	1
RGP	REGENCY ENERGY PARTNERS L P	1
UPL	ULTRA PETROLEUM CORP	1
GLUU	GLU MOBILE INC	1
EPE	EP ENERGY CORP	1
GPRO	GOPRO INC	1
ARIA	ARIAD PHARMACEUTICALS INC	5
DWA	DREAMWORKS ANIMATION SKG INC	6
SPWR	SUNPOWER CORP	7
SHAK	SHAKE SHACK INC	8

Conclusion

We introduce the Short Squeeze model to systematically score stocks based on their potential for a short squeeze event. Our model incorporates capital constraint indicators – Out-of-the-money Percent, Out-of-the-money Percent 20-day Maximum and Short Position Concentration – constructed using short loan transaction data from our Securities Finance dataset to identify names where short sellers have increased potential to cover positions. We also find that certain events, including earnings announcements, positive news events identified from RavenPack and abnormal trading volume, increase the probability of a short squeeze.

We test model efficacy in terms of its short squeeze predictability during the in-sample period. Based on our model scores, we find that squeezes occurred 1.67% of the time in D1 which isolates names most likely to squeeze. In other words, there is a 78% greater likelihood than the base universe at 0.94%. Furthermore, the occurrences decrease in general across deciles with D10, representing names least likely to squeeze and exhibiting the lowest occurrence.

Next we consider application of our model in terms of its alpha generating capabilities. Stocks with the highest probability to squeeze outperform the universe for open-to-close returns, with an additional 7 bps of return on average versus the universe and 12 bps versus names least likely to squeeze. Positive returns extend out to 1-month holding periods with 44 bps and 103 bps of additional alpha, respectively. Additionally, the model produces positive D1 excess returns in the out-of-sample period.

The model can also be used to improve alpha forecasts based on several well-followed short interest measures. The Short Interest Ratio sees an improvement on average return spread from 0% to 0.189% monthly. The short interest position also improves from 0.352% to 0.447%. Using our Securities Finance data on shares on loan to shares outstanding, we again see an improvement from 0.304% to 0.456%.

Our final application uses the Short Squeeze model as an overlay to our existing US multi-factor strategies. The models see modest improvement in both mean return spread and information ratio in general, with the Relative Value model improving the most as measured by both the mean return and information ratio. The Value Momentum Analyst 2 model improves by 0.67 on the information ratio, revealing a large decrease in risk.

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Appendix

Background

Short selling refers to sale of a security that the seller does not own, where the delivered security is borrowed by the short seller. The intention is to buy the security at a lower price in the future. In order to lock-in profit, or to avoid further losses (where the price of the security has gone up), short sellers need to cover a short position which involves buying securities in the market and returning the borrowed stock to the lender. The short seller may also be forced to cover positions due to failure to meet a margin call or when the security lender recalls the stock.

Short sellers need to deliver the stock on settlement day, in the same way as any other trade. Since they do not own the stock, they have to borrow it or face penalties for a failed trade. Naked short sales (where the security has not been located and/or borrowed in advance) are now banned in most jurisdictions across the globe. As a result, short sellers almost always need to borrow stock, and as such the resulting lending data provides a close proxy for short selling volumes.

Securities lending is a market practice whereby securities are temporarily transferred by the lender to the borrower. The borrower is obliged to return the securities either on demand or at the end of any pre-agreed term. Securities lending operates as an over the counter market. Our Securities Finance data provides benchmarking and transparency for participants in the securities lending market by capturing the daily supply, demand, and borrowing costs of individual securities. Information is sourced directly from leading industry participants including prime brokers, custodians, asset managers and hedge funds.

Our Securities Finance data covers more than 3 million intraday transactions, spanning $15.5 trillion of securities in the lending programs of over 20,000 institutional funds globally. This dataset includes a wide range of securities lending metrics collected on a daily basis. It provides content on the securities lendingmarket including daily shares borrowed, inventory of available shares on loan, level of utilisation, loan concentration and stock borrowing costs. It captures around 90% of the securities lending market in developed markets. The coverage can be lower for emerging and frontier areas where the securities lending market is not yet fully developed.

Short squeeze definition

Short selling refers to the sale of a security that the seller does not own, where the delivered security is borrowed by the short seller. The intention is to buy the security at a lower price than that at which the security was sold short. When the price of the security rises, the short seller can incur significant losses as the downside potential due to a price rise is unlimited.

In order to lock-in a profit, or avoid further losses (where the price of the security has gone up), short sellers need to cover a short position. This involves buying securities in the market and returning the borrowed stock to the lender. The short seller may also be forced to cover positions due to failure to meet a margin call or when the security lender recalls the stock. The resulting buying pressure can drive prices higher in a phenomenon known as a short squeeze.

While fears of a short squeeze may act as a constraint on short sale activity, particularly in the event of manipulative short squeezes by original buyers who would benefit from inflated prices, the role of short sellers is considered a vital market practice to keep stock prices in-line with fair value.

The actual occurrence of a squeeze is a debatable subject. One such issue arises from general informed market trading activity which can easily be misconstrued as a short squeeze. As such, there is a clear need to identify specific characteristics to isolate their existence. However, many differing definitions are used in practice, forcing the need for a systematic identification process.

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We outline the following steps in our definition of a short squeeze to systematically isolate their occurrence:

Pre-squeeze : Filter out securities ranked in the bottom quintile of Demand Supply Ratio and Implied Loan Rate. These factors are primarily used to identify securities that are heavily shorted. Demand Supply Ratio categorises stocks that are heavily borrowed in the market relative to the lendable inventory of that stock and Implied Loan Rate measures the cost of borrowing which is indicative of the shorting flow. Stocks are ranked in a percentile form (1- 100) on a relative basis by universe. Those securities having the best (worst) factor scores are assigned a 1 (100). Therefore, the closer a rank is to 1 (100), the more (less) prominent is the investment style for that stock.

For robustness, we also apply a proprietary Securities Finance algorithm to filter out positions associated with a dividend arbitrage trade. One well-documented bias in securities lending data is related to dividend arbitrage activity. Raw securities lending information is affected by this phenomenon and we take special care to remove any bias. The execution of such a transaction ultimately results in a gradual increase in the demand (and cost) to borrow a stock around the dividend record date as firms hedge the associated market risk. This clouds the ability to detect negative sentiment around company prospects. For example, it is prevalent in European stocks as taxation policy there is highly fragmented.

Short squeeze: Identify situations where a stock's price increases significantly over a 3-day period (i.e., a 3-standard-deviation move relative to the prior 60 trading days) as we know that a surge in price could be staggered and last for a few days depending on the news announcement and the degree of positive sentiment. Also, stock recalls are settled in the same way as stock purchases (i.e., borrowers have 3 business days to return the stock).

Post-squeeze: Include only securities that are heavily shorted and the potential squeeze event is followed by a decrease in the shares on loan. In our definition of a short squeeze, we identify securities that have had a recent price surge and are heavily shorted. This should be accompanied by a reduction in stock loan quantity over five consecutive days. One could argue that returns of securities could reflect price manipulation that is characterised by large positive abnormal returns in the absence of any news announcements; however, we reduce the possibility of including any price manipulations in this step.

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