LUND UNIVERSITY FINANCE SOCIETY EST 1991

TRADING & QUANTITATIVE RESEARCH REPORT

ALTERNATIVE DATA

Quantifying & Utilizing Unorthodox Sources of Financial Information

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OQAM

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Introduction & Scope

Introduction

Alternative data is the data that cannot be found in the financial statements or the stock performance of a company. Some examples of this are credit/debit card data, web data, social media sentiment, insider transactions, short positions, and even satellite information in some cases [1]. Today, an increasing amount of hedge funds and asset managers are in pursuit of alternative data to aid in their investment and trading decisions. Relationships can be found between the data and company revenues and stock performance, which can be used as signals preceding upward or downward movements in equity prices. Success has been found with these methods by companies such as Renaissance Technologies, which is a quantitative investment management company that uses big data to perform systematic trading [2]. This can partly be said to be based on the Efficient Market Hypothesis (EMH), particularly the semi-strong form, which states that market prices reflect historical prices and all publicly known information, but not information that is private or mostly unknown by the general public. Particularly in looking at the effects of insider trading on equity prices, in general it has been found that stocks which are purchased by insiders generally outperform those from a random sample [3]. This refutes the strong form of the EMH and points to potential gains by exploiting this type of information. As this data is published shortly after the transactions, the market is likely to react within a timeframe of days, but the full information may not be reflected until the next quarterly report or press release. Thus, in this analysis timeframes that include these two alternatives are considered. This project sought to use these insights to predict equity price changes using alternative data in the form of short positions and insider transactions, as prescribed by the "quantamental" asset manager OQAM. Quantamental refers to using a mix of quantitative and fundamental analysis to make investment decisions.

Definition

The project plan proposed by OQAM stated that the objective of the project was to analyze if short positions and insider transactions can be used to predict single stock equity price movements relative to the general market in periods of 1, 5, 20 and 100 days. Then, to suggest an investment model based on the findings. The equities in the analysis were single stock equities included in the OMX Stockholm Benchmark Index (OMXSBGI), and this index was also used as a benchmark in the analysis. As suggested by OQAM CIO Thorbjörn Wallentin, the alternative data sets on historic significant short selling and insider transactions were built from publicly available data provided by Finansinspektionen (FI), the Swedish financial supervision authority. The goal was to research whether short selling data or insider transaction data could be used in equity price movement predictions.

The investment model proposed provides predictions for downward and upward moving prices using each respective dataset. The hypothesis relating to the historic short positions data is that downward price movements could be predicted after short positions were entered.

In this analysis, the short positions were sorted into high, medium and low price shorts and subsequently a trading strategy was implemented with the expectation that short trades made after high price shorts would generate superior returns. For the insider transactions, only the acquisition transactions were considered in the analysis, as background research points to the greatest insight from insider transactions is from acquisitions [4, 5], and that they were roughly 10 times more common than insider sales in the data set. The hypothesis for the price relationship in this case was that there will be a greater upwards movement of the price compared to the benchmark in the timeframes mentioned above, measured by the average return after a significant amount of insider acquisitions.

Scope & Data

The single stock equities that were considered in the analysis were the 92 stocks that comprise the OMXSBGI. Historical daily resolution price data for these equities was downloaded from Bloomberg in OHLC format, including the volume weighted average price (VWAP), and dates from 01/01/2010 to 20/10/2020. VWAP was selected as this is a measure of a general price in the market, which helps generalize the long-term trend in price. The benchmark index daily price data was also downloaded. The price used in the analysis was an average of the daily high and low and had the same date range as the single equities.

In order to evaluate the impact of significant short positions initiated against an equity, historic short selling data was downloaded from FI. This dataset listed all the historically significant short selling positions, i.e., those that exceeded 0.5% of the volume of issued shares of a stock. This referred to entries of short positions over time, so an entry of 1% on a certain date meant 1% of the total stock volume was being shorted at that time; if another later entry by the same party was 2%, this meant an additional 1% of the total shares have been shorted (net 2%) by this party. Conversely, a decrease in the short position would be shown as a later entry with a lower position percentage by the same party. This data set contained the equity shorted, the issuer of the trade, the ISIN (International Securities Identification Number) code of the stock, the percentage of the position, and the date of the trade in daily resolution (short positions must be reported the same day they are made). The data set ranged from 10/05/2010 to 08/10/2020 in daily resolution [6].

The insider transaction data was downloaded from FI using a self constructed Java program with the help of an open-source library called Insynsregistret. This was needed to download the entire data set, since FI only allows the export of 1000 rows at a time. The data set included the publication date of the transaction, the issuer, the person discharging managerial responsibilities (PDMR), their company position, whether they are closely associated to the equity in question, the nature of the transaction, transaction date, price, volume and trading venue. This data set stretched from 04/07/2016 to 14/10/2020 and was also in daily resolution [7].

Method

The investment thesis in this analysis presents two predictions of the price direction based on the two different data sets, with short positions being related to the downward direction (in red) and insider acquisitions to the upward direction (in green), as can be seen in Figure 1. Before each analysis, data preprocessing was conducted, also described in Figure 1.

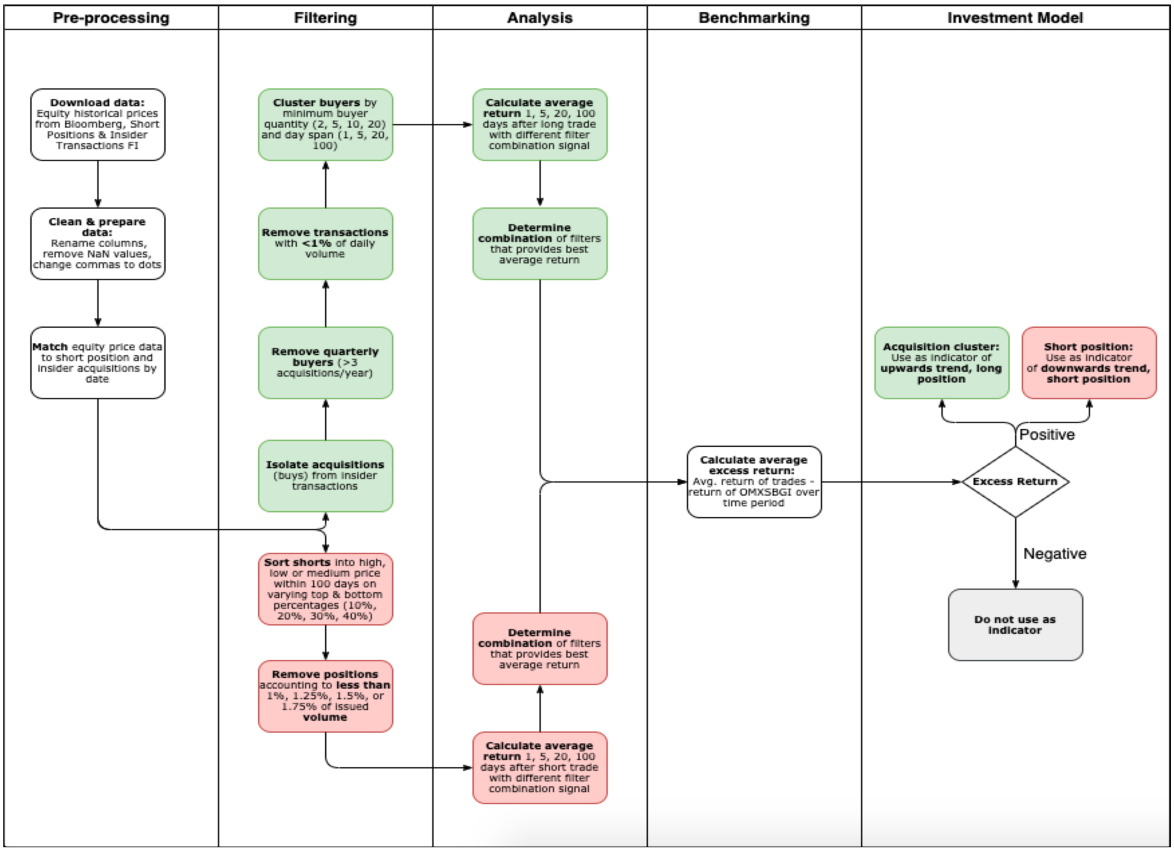

Figure 1. Project Process Flowchart.

The hypothesis behind the analysis of the short position data was that the public knowledge of the initiation of a major short position would affect the price of the stock negatively, and this was measured in time frames of 1, 5, 20 and 100 days after the position. In order to test the expected negative relationship between short positions and price returns, the data was filtered to see clearer patterns. As can be seen in Figure 1, the two filters were the percentage price level of the short and the percentage minimum size of the short. The short positions were split up into three groups, "high", "low" and "intermediate" price shorts. This refers to shorts that were at the highest or lowest 10% (or 20 %, 30 %, 40% - we call these percentages "margins" in what follows) of prices within the last 100 days, and those in between those price levels. The minimum size (as a percentage of issued volume of stock) for it to be regarded as a sell signal was varied (min. 1%, 1.25%, 1.5% and 1.75%). To test the significance and validity of the hypothesis, the same analysis was also performed for shorts that were initiated at historically "low" and "intermediate" prices.

The success of the trades was quantified by considering the returns on the fictional investments needed to buy the stocks that were shorted according to the strategy. These returns were then put into a form fit for comparison and analysis by calculating their "excess returns". The excess returns being the return on trade minus the returns on the comparison strategy, which consisted of simply shorting the index (OMXSBGI). An example of trades based on one of the strategies is shown in Figure 2.

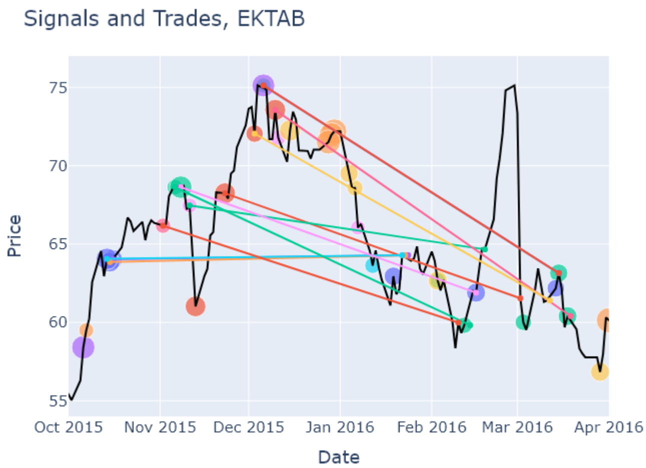

Figure 2. Visualization of the short selling strategy. Dots represent historical short positions (different colors: different holders, different size of dot: different size of position). The straight lines represent the trades initiated after suitable signals (left end of line: beginning of trade – in connection with a historical position, right end: end of trade – 100 days later). The strategy here is to act on "high" price shorts with 20% margins and min size of 1%.

Method

For the insider transaction data, the hypothesis was that the public knowledge of a cluster of insider acquisitions would trigger an upwards movement of the price under time frames 1, 5, 20 and 100 days after the publication date. Thus, all other transactions apart from acquisitions were filtered out of the dataset. Three filters were applied and varied on this data set in order to determine the combination of filters that would reap the best average excess returns compared to OMXSBGI index return under the same period. As seen on Figure 1, the first filter was removing quarterly buyers or those under incentive plans by the company in question, so acquisitions by the same party of more than 3 times per year were discarded. Then, transactions which accounted to less than 1% of the daily traded volume were discarded in order to identify stronger acquisition signals. Finally, the clustering filter was applied, which had two dimensions: A time frame of trading day spans, and minimum number of buyers within this time frame. The combinations of this filter analyzed were time frames of 1, 5, 20 and 100 trading day spans, and 2, 5, 10 and 20 minimum buyer numbers, as these were combinations where there were a significant number of clusters. Note that the days considered in the cluster filter is in which time frame a certain minimum amount of insider buys need to occur in order to generate a signal.

A representation of the cluster filter in action can be seen on figure 3, 4 and 5. Figure 3 shows the VWAP of TELE2, and only has the quarterly buyer filter applied. The upward green triangles represent an insider acquisition. Comparing these to Figure 5, which shows the data frame of insider acquisitions, index 1 is removed due to the quarterly filter. In Figure 4, which is also for TELE2 under the same time period, indices 1, and 9 are further removed as here the cluster filter with the parameters of 5-day span and minimum 5 buyers is added on, and these points are outside the 5 trading days. The cluster is highlighted in green, and a long position would be entered at the end date of the cluster.

The returns were measured as if the stock was bought at the VWAP the day that a buy signal was generated compared to the VWAP of the stock after 1, 5, 20, 100 days. As the VWAP is an average of the daily price, no delay between the signal and the purchase of the stock was considered, as there was an assumption that the purchase could be made in the same day as the signal, by using higher resolution live data when trading.

The returns of the buy signal mentioned above were calculated for datasets filtered with different filter combinations (accounting to 8 data sets in total, 4 data sets with clusters). These were then averaged and compared to the return of buying and holding a position in the OMXSBGI index (using the daily average of the high and low price of the index) at for the same time period to obtain the average excess return of each filter combination.

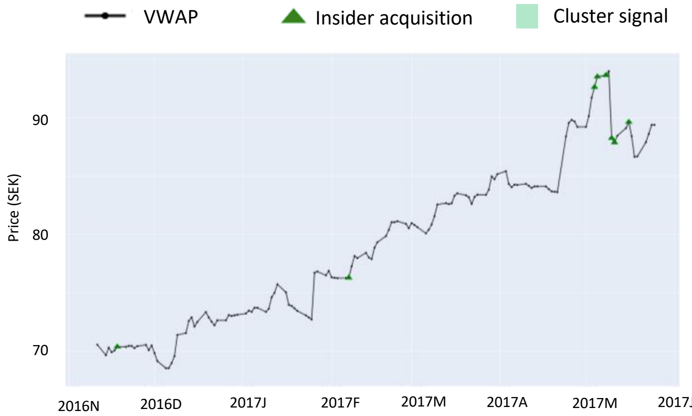

Figure 3. Snapshot of TELE2 VWAP and insider acquisitions with quarterly filter.

Figure 4. Snapshot of TELE2 VWAP and insider acquisitions with quarterly and cluster filter.

	Publication Date	Issuer	PDMR	Nature of Transaction	Volume_x	Price	Currency	VWAP
0	2016-11-18	Tele2 AB	Guillaume van Gaver	Acquisition	562.0	53.00	SEK	70.3449
1	2017-02-07	Tele2 AB	PER LARS NORDMARK	Acquisition	8000.0	76.40	SEK	76.2627
2	2017-05-04	Tele2 AB	Fredrik Stenberg	Acquisition	6139.0	0.00	SEK	92.6261
3	2017-05-04	Tele2 AB	Stefan Backman	Acquisition	6139.0	0.00	SEK	92.6261
4	2017-05-05	Tele2 AB	Fredrik Stenberg	Acquisition	6139.0	0.00	SEK	93.5343
5	2017-05-08	Tele2 AB	Viktor Wallström	Acquisition	6139.0	0.00	SEK	93.6554
6	2017-05-08	Tele2 AB	Malin Holmberg	Acquisition	6139.0	0.00	SEK	93.6554
7	2017-05-10	Tele2 AB	Samuel Skott	Acquisition	6139.0	0.00	SEK	88.2534
8	2017-05-11	Tele2 AB	Georgi Martin Ganev	Acquisition	1030.0	88.40	SEK	87.8792
9	2017-05-16	Tele2 AB	Edward Alm Gerentz	Acquisition	300.0	88.65	SEK	89.6351

Figure 5. Insider acquisition data frame for TELE2 for figure 3 and 4.

Results – Short Trades

As described in the method section, the short trades were classified depending on at which price they were initiated historically speaking. The return on each trade was then calculated for different time horizons: 1, 5, 20 and 100 days after the trade. The return of shorting the benchmark index (OMXSBGI) under the time the trade was held was subtracted from this return. Finally, the resulting returns adjusted for the index were averaged over the number of trades. The results, presented as heat maps, for the “high”, denoted (H) and “low”, denoted (L), shorts, can be seen in figures 6 a) – f) .

For brevity, the plots depicting the results for the 5-day time span have been omitted (they contain data very similar to the 1-day plots). The “intermediate” price strategy plots have been moved to the appendix and can be found in figure 14. Additional plots showing the number of trades that went into producing each of the boxes of figures 6 and 14 can also be found in the appendix, figures 11 – 12.

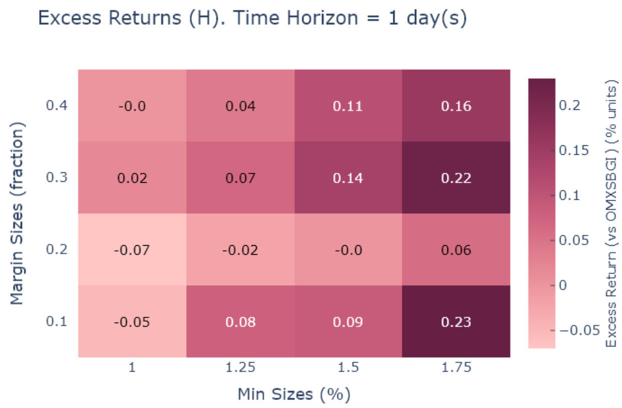

Figure 6 a)

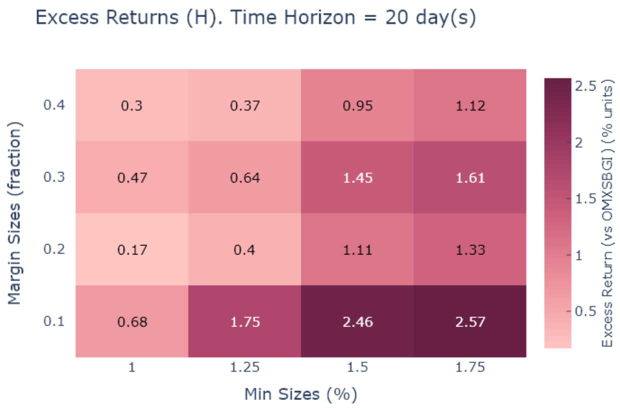

Figure 6 b)

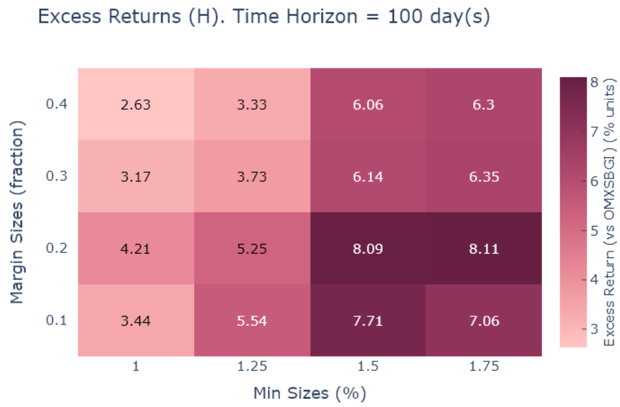

Figure 6 c)

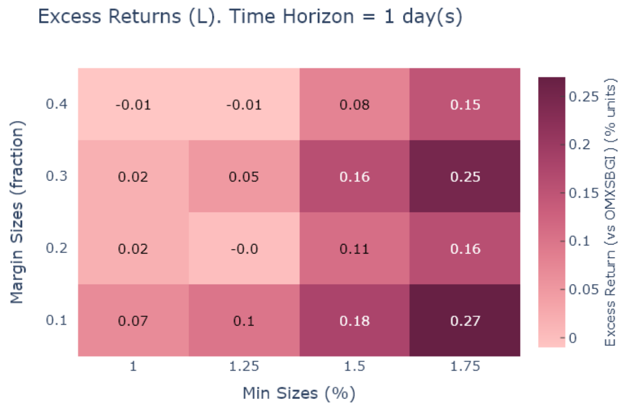

Figure 6 d)

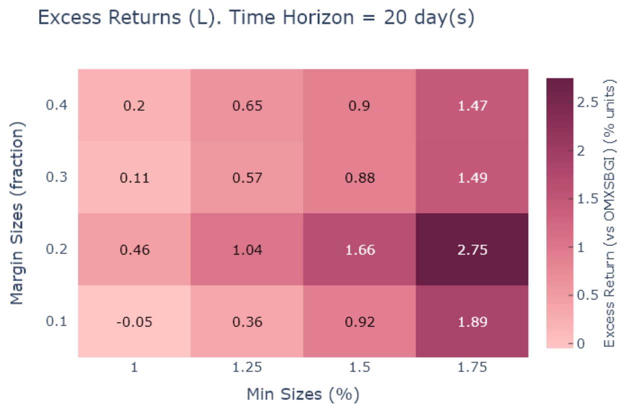

Figure 6 e)

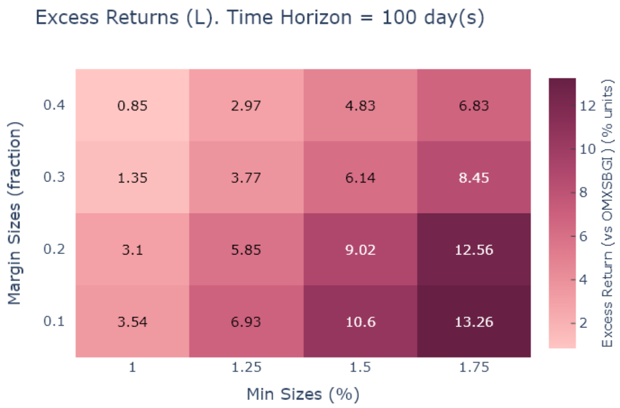

Figure 6 f)

Figure 6, a) - f). Average profit on the trades, minus the profit of shorting the benchmark (OMXSBGI) under the same period. In figures a) to c) the “high” price shorts are used as signals, with the y-axis specifying the margins and the x-axis specifying the minimum size of the signal historical position. In figures d) to f) we have the same scenario but now with “low” price shorts used as signals.

Results – Insider Acquisitions

Figure 7 shows four heatmaps displaying the average excess returns after 1-, 5-, 20- and 100-day holding periods of all trades with all three filters applied. Quarterly transactions and transactions under 1% of the daily volume were removed from the insider acquisition data set, and the transactions were clustered based on day span and minimum buyer dimensions. Thus, each rectangle represents the average excess returns of the trades made after identifying a cluster that comprises of a combination of a time frame of 1, 5, 20 or 100 days (y axis), and a number of minimum transactions (x axis) found within the time frame (2, 5 or 10). Note that empty rectangles indicates that no cluster signals were identified with the given day span and minimum buyer parameters, and thus no trades were made. The other 3 combinations with the cluster filter can be found in the Appendix. A positive average excess return would signify that on average, trades made after a cluster signal outperformed the average of holding the OMSXBGI index for the same time period as each trade. Thus, a negative excess return does not necessarily mean a negative return, only that the return of the trades was less than that of the benchmark. However, underperforming the index means that pursuing the strategy is not worth the effort, as simply holding the index has a better result. Similarly, an excess return close to zero means the strategy does not have a meaningful benefit compared to buying and holding the index.

Figure 8 shows the number of trades in each cluster combination bucket. This is the same for all time frames, as the same number of signals are traded on, but held for longer or shorter to test if the holding period of the trades affects the excess returns.

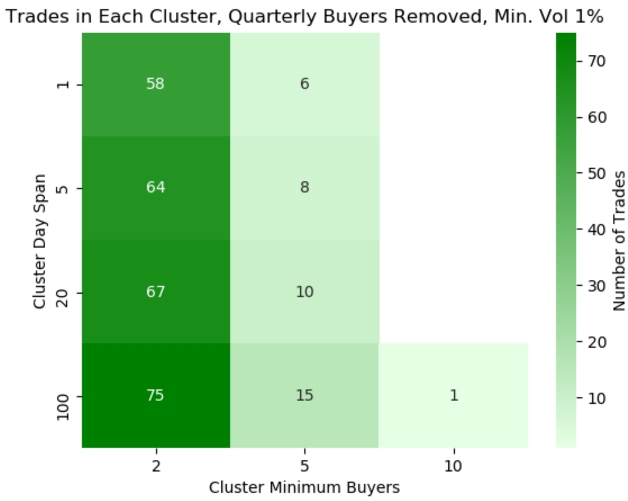

Figure 8. Number of trades after insider acquisition clusters combinations, with quarterly buyers removed and only acquisitions >1% of daily volume considered (all filters applied)

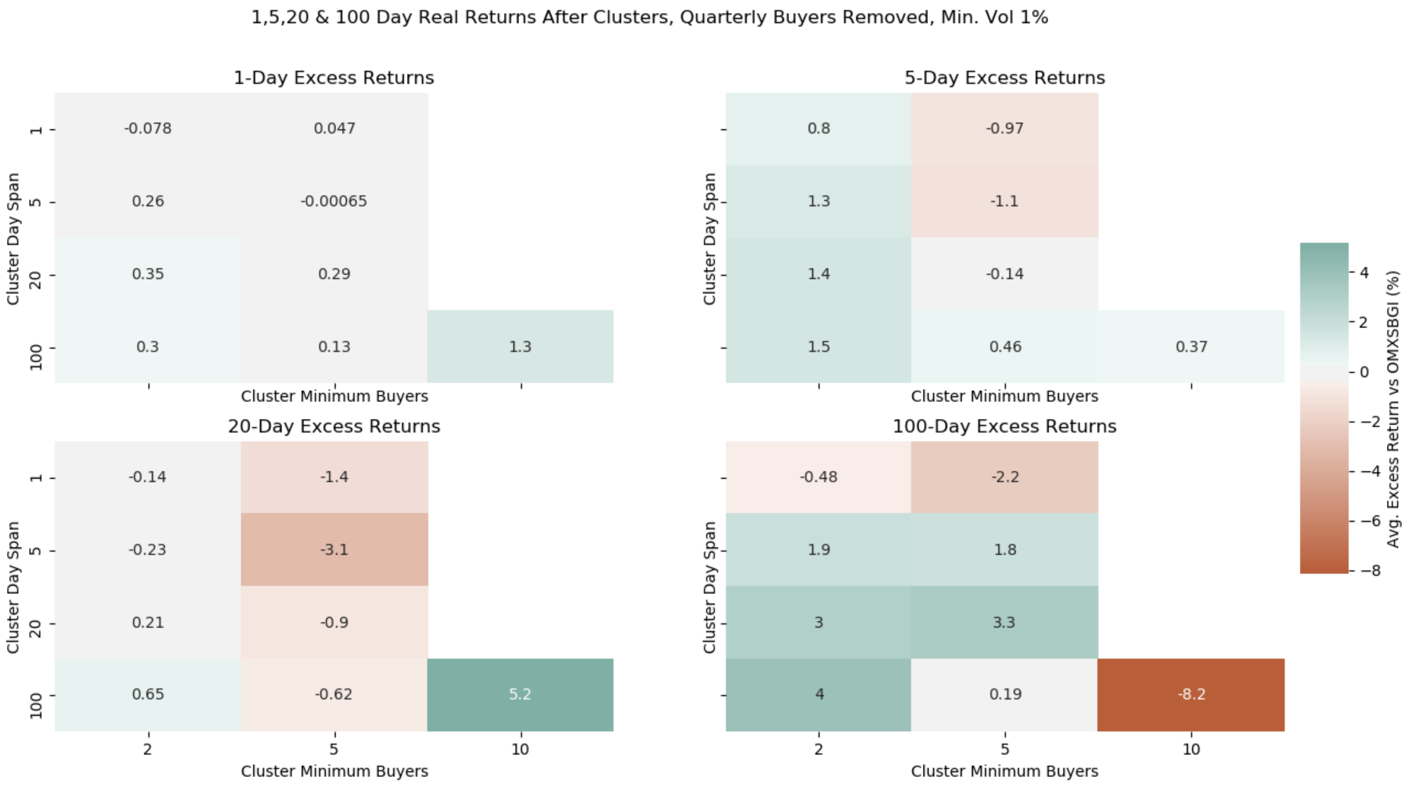

Figure 7. Heatmaps of average excess percentage returns (avg. of trade return - OMXSBGI return) in 1-, 5-, 20- and 100-day holding periods of long positions after insider acquisition clusters combinations, with quarterly buyer acquisitions removed, and only acquisitions >1% of daily volume considered (all filters applied).

Results – Insider Acquisitions

Table 1 shows the excess returns of trades made with other combinations of filters, excluding the clustering filter. The trades with these filters thus were made after every insider acquisition that was not removed by the filters, and were held for 1, 5, 20 or 100 days. This explains the much greater number of trades. This table helps to understand if the clustering filter makes a positive impact on the excess returns of the trades. Further, if any particular filter is affecting the performance negatively or positively.

Filters	Trade Count	1-Day Average Excess Return %	5-Day Average Excess Return %	20-Day Average Excess Return %	100-Day Average Excess Return %
No filters, trading after every acquisition	4903	0.078	0.135	-0.433	1.780
Only remove acquisitions by quarterly buyers	1341	0.264	0.483	0.179	2.539
Only remove acquisitions <1% of daily volume	1210	-0.001	0.206	-0.331	1.333
Remove both quarterly buyers & <1% volume acquisitions	330	0.206	0.591	0.506	1.600

Table 1. Average excess returns of all filter combinations excluding the cluster filter for holding periods of 1, 5, 20 and 100 days

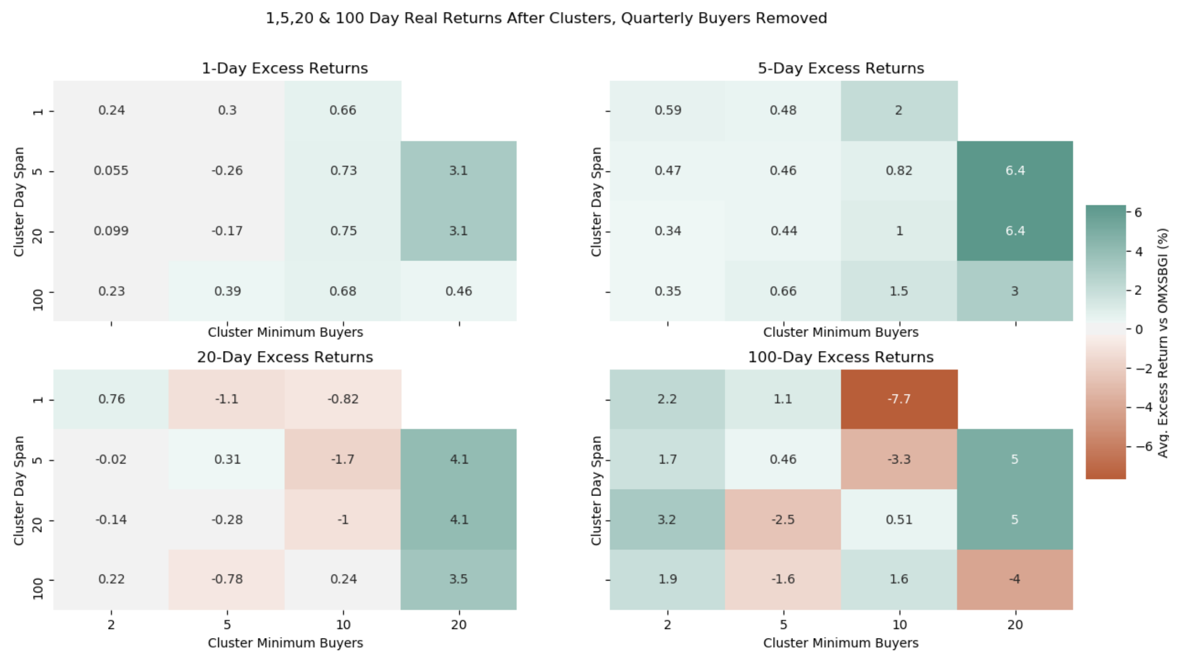

Figure 9. Heatmaps of average excess percentage returns (avg. of trade return - OMXSBGI return) in 1-, 5-, 20- and 100-day holding periods of long positions after insider acquisition clusters combinations, with only quarterly buyer acquisitions removed (cluster & quarterly filter)

To showcase another filter combination including the cluster filter, Figure 9 shows the cluster filter with the quarterly filter, which adds an additional column of minimum buyers, and increases the number of trades in each bucket, as seen in Figure 10. Here there is a much higher maximum excess return value in the new buckets but note that these only hold 1 to 4 trades. However, buckets in the 2 minimum cluster buyer column show significant excess returns in the 100-day holding, with a much greater number of trades than with all filters applied, seen in Figure 7.

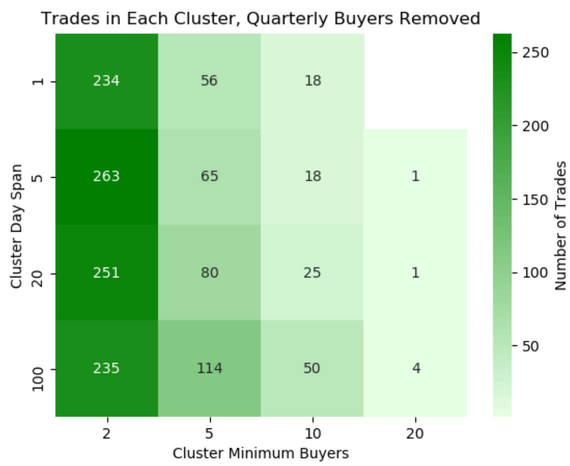

Figure 10. Number of trades after insider acquisition clusters combinations, with only quarterly buyer acquisitions removed.

Analysis

Significant Short Trades
From Figure 6 we see the following trends: As expected, bigger short positions are better predictors of stock performance. The holding period that worked best in this "high" strategy was the 100 – day holding period (Figure 6c). The 20-day holding period in Figure 6b was also overperforming compared to the market, but at a lower level than the 100-day period. This could potentially be a better alternative in practice as trades could be exited more frequently freeing up capital for additional trades, thus increasing the cumulative returns. However, to test this, a simulation of capital allocation would have been needed, and this was not done for this report. Although it is evident that shorts of size >1.5% are preferable, it seems that using only very large shorts (>1.75%) as signals does not yield superior returns. One possible explanation for this, is that we are not looking at unique shorts in this analysis. It is therefore possible, that large proportion of the large shorts are actually due to an increase in existing short positions. This is supported by our investigations in how the short positions evolve over time. Hence, in the case of the shorts in Figure 6c it might have been the case that a portion of the anticipated fall of the stock price already took place and the actors holding those short positions were increasing their short positions to increase their potential profits, as the price decrease was occurring. Thus, those shorts would still be profitable, but the profit would be percentually similar to the case of the earlier (smaller) shorts. Furthermore, one can observe that using very stringent criteria on what is considered to be a historically "high" short is also not to be preferred in this scenario.

In the other scenarios that were tested, where historically "low" and "intermediate" shorts were used as signals, we can also observe a partial confirmation of our hypothesis. As expected, "intermediate" shorts are poor predictors of stock performance and trades initiated based on them underperform compared to index except for a few parameter combinations (Figure 14). Even for those parameter combinations that yield positive excess returns the profit is significantly lower than the corresponding "high" scenario. The medium shorts underperform in almost every combination in shorter holding periods as well which is why they were not explored further. In the "low" scenario however, we see that on a longer time scale (Figure 6 f), considering only large shorts (>1.5%) and strict margins (10–20 %) the trades actually also significantly outperform the index (actually more than the "high" trades). Therefore, this seems to be the best strategy. Curiously, in the same figure we see that for other parameter combinations, the "low" strategy either generates similar or inferior excess returns compared to the "high" strategy.

Insider Acquisitions
Figure 7 shows the returns after 1, 5, 20 and 100 days compared to the OMXSBGI for the different cluster parameters with all filters applied. In total, there were 304 long trades between 04/07/2016 and 14/10/2020 applying the quarterly buyer filter and volume filter to different cluster parameters.

Our hypothesis was that the more insiders buying in a shorter time span would give a stronger positive signal, however this was difficult to confirm in the figures, as less data points exist the more constraints we add. As an example, for a minimum of 10 buyers no trades exist for 1-, 5- and 20-day clusters and there was only one trade for 100-day clusters. Furthermore, the additional minimum buyer parameter of 20 that we tested for had no trades at any day span, thus removing this column all together. Acting on a signal with too little data carries a big risk of overfitting. Besides running the risk of overfitting there is a chance that a very constrained signal might not occur frequently enough to be worth pursuing. Just because a signal is considered stronger it does not necessarily lead to better returns due to fewer opportunities.

On the other hand, there seems to be a pattern emerging when looking on at least two buyers and increasing the cluster time span. The combination of 100 cluster day span and at 2 minimum buyers has the greatest number of trades of all the combinations and outperforms the OMXSBGI for all holding periods, as seen in the bottom left rectangle in each of the heatmaps in Figure 7. To conclude, there is a compromise between generating what we believe is a stronger signal and having the data to support it.

A clear insight from the results is that the average returns for each cluster combination overall increase the longer the holding period. Figure 7 (1-day return) and (5-day return) have a maximum excess return of a couple percentage points above 1, meaning that they outperform the OMSXBGI index by 1 percentage point. However, this is increased to 5 in (20-day return), and 4 in (100-day returns). This could potentially be explained by information known by insider parties being "leaked" to the general market through quarterly reports and other company filings, which would be better reflected under the 100-day period.

Table 1 shows the filter combinations that exclude the clustering, so this is one dimensional data. The excess average percentage return is also the highest here for all filter combinations at 100 days. Furthermore, all filter combinations beat the OMXSBGI in this time frame. However, adding on additional filters does not increase the returns for all time periods. The holding period of 5 and 20 days were the only periods where applying all filters gave the highest returns.

Only applying the volume filter to the data actually gave the lowest excess returns, underperforming in 1-day and 20-day holding periods. The best combination seems to be only applying the quarterly buyer filter at every time frame, followed by all filters except for in the 100-day period, where no filters are in second place. This could mean that the volume filter may be too strict. Comparing this to Figure 7, adding the clustering filter significantly improves average returns especially in the shorter time periods, however we have much less trades in the most promising buckets compared to the trade volume without this filter.

Analysis Cont. & Conclusions

Insider Transactions Analysis Cont.

Applying the insights of the one-dimensional filters in Table 1, an option could be to remove the volume filter from Figure 7. This alternative can be found in Figure 9. The 100-day average excess returns on Figure 8 includes only two filters and has an excess return of 3.2% in the 20 day-span, 2 minimum buyer bucket, with 251 trades. This could be a promising strategy going forward for a longer time horizon.

Figures 15 and 16 in the Appendix confirm the insights from Table 1. Trading with only the cluster filter is slightly better than with no filters but performs worse than Figure 7 or 9, although with a higher trade volume (Figure 17). Trading with the cluster and volume filter is the worst combination with only a few buckets outperforming with a percentage greater than 1, but with few trades in the best ones, and worse than Figure 7 and 9 as well. There were two outlier trades that had a 62% average return but there was only 1 trade in each bucket in that case (Figure 18), making this an unreliable result.

Conclusion

To summarize the investment model proposed in this report, both a signal to enter a short position, as well as a long position are proposed.

The short signal would be when a significant short position of at least 1.5% of the total floated stock is entered, when the stock price is at in the 10-20% high or low level of the historical price in the past 100 days. The best holding period for the short for this signal would be 100 days, which has been shown to outperform holding a short position in OMXSBGI.

For the long position signal, for a 5-day holding period, the best performing strategy would be be to go long after a cluster of at least 2 insider acquisitions have been identified within 20 or 100 days, given that it is not a quarterly or incentive acquisition, and that none of the acquisitions make up less than 1% of the day's volume. This resulted in a 3% and 4% average excess return over 64 and 75 trades respectively over 3 years. For a holding period of 100 days, going long after a cluster of at least 2 insider acquisitions within 20 days, but only removing quarterly buys, is the best performing strategy. This resulted in 3.2% excess return on average over 251 trades over 3 years.

A consideration regarding the holding period of the trades was that while the excess returns were the greatest under the longest holding period tested, there is a sort of opportunity cost tied to this. If instead of holding for 100 days, numerous 5-, or 20-day trades were made, the cumulative return could be greater than for the single trade. Thus, a way to normalize for this would have been to divide the returns by the number of holding days. However, speaking to Thorbjörn from OQAM, it was decided that this analysis was not necessary since practically the absolute average excess return was more relevant than producing a "normalized" result.

Some limitations to this analysis were the range of the data used, especially for the insider transactions analysis. The data was only available from 2016, and it ranged up to October 2020. Therefore, this backtest mostly considers a quite bullish period in the market, as well as a "black swan" crash of sorts due to the COVID-19 pandemic, which could be said to not be typical market behavior. Testing on a larger sample could reveal the chosen strategy to be less effective. To test the validity of the strategy, running a backtest on data from October 2020 up until now, February 2021, could give a sense of the success outside the given data sample, however this was not done due to time constraints. Further improvement would be to acquire data before 2016.

Further, a change in the quarterly filter to make this more precise to what the intention of the filter was could improve the results. The current filter only removes transactions if the same buyer had more than 3 transactions each year. While this is meant to remove quarterly and incentive buyers, the filter could also remove frequent voluntary buyers, which could be a signal that is missed. Instead, the filter could perhaps check for similarities in the frequency pattern of the same buyer, and if these match for two consecutive years, remove the transactions by that buyer.

Another statistic to help evaluate the strategies would have been the standard deviation of the excess returns. There is some indication of the variability of the trades under the filters while looking at the heatmaps, but the variance within each bucket is not reflected. Thus, a bucket could have a quite good average excess return, but there could be trades in that bucket that had quite negative values but were normalized as the results were averaged.

An addition to this model, which was considered but not executable within the project timeframe, was including sentiment analysis to confirm a buy or sell signal. The analysis could entail scraping Twitter data on the stocks analyzed in this paper and using a language processing model to evaluate positive or negative sentiment. Based on this, if a stock had a trading signal suggested by the existing strategies, the trade would only be executed if the sentiment matched the direction of the trade (positive for long, negative for short).

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Appendix

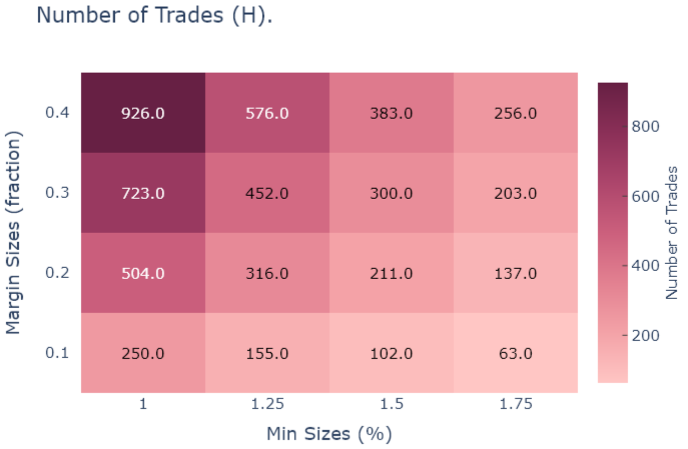

Figure 11: Number of trades in the "high" strategy.

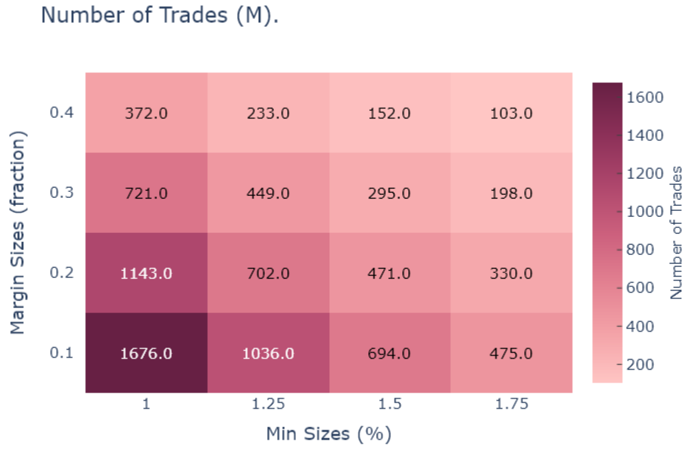

Figure 12: Number of trades in the "intermediate" strategy.

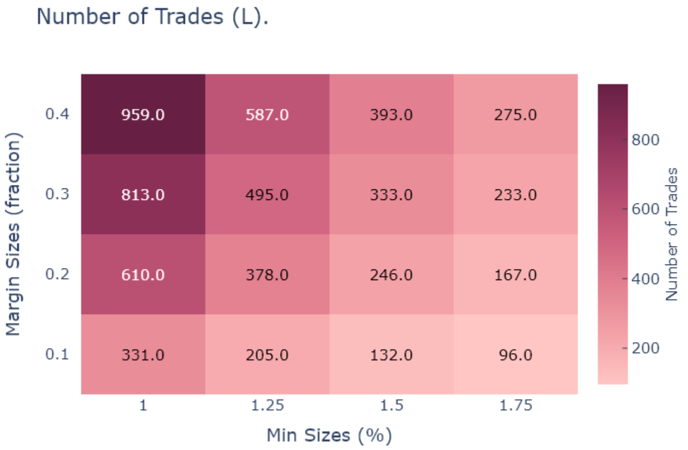

Figure 13: Number of trades in the "low" strategy.

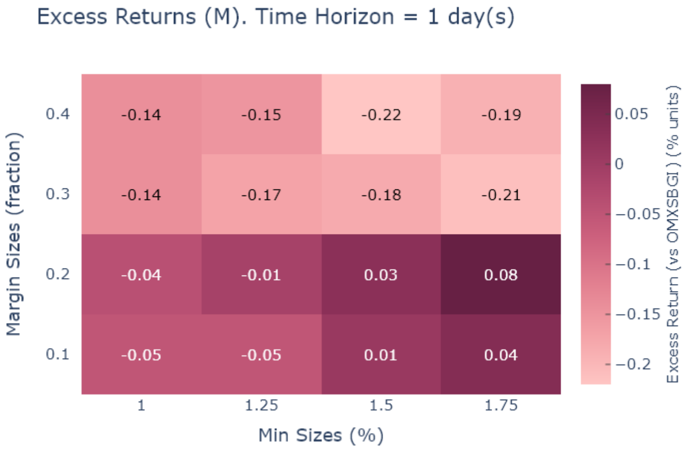

Figure 14 a)

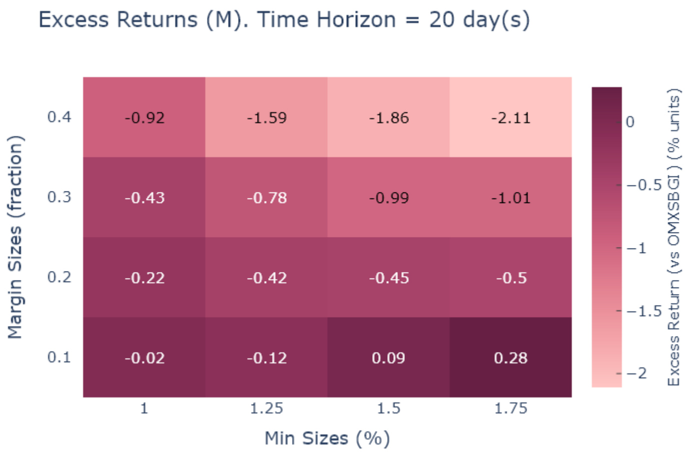

Figure 14 b)

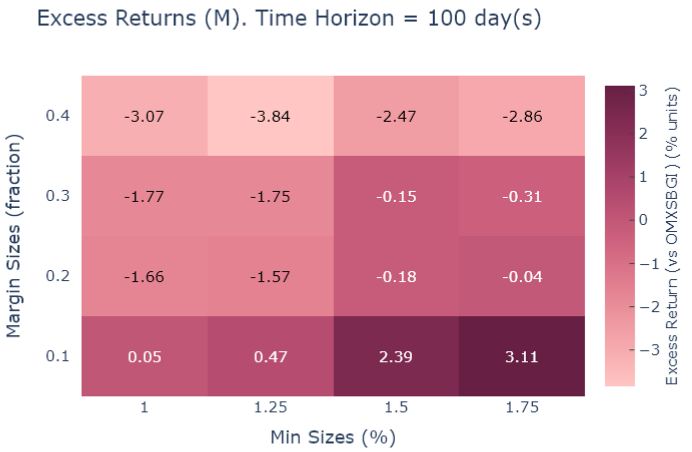

Figure 14 c)

Figure 14 a) – c): Average profit on the trades, minus the profit of shorting the benchmark (OMXSBGI) under the same period. The "intermediate" price shorts used as signals, with the y-axis specifying the margins and the x-axis specifying the minimum size of the signal historical position.

Appendix

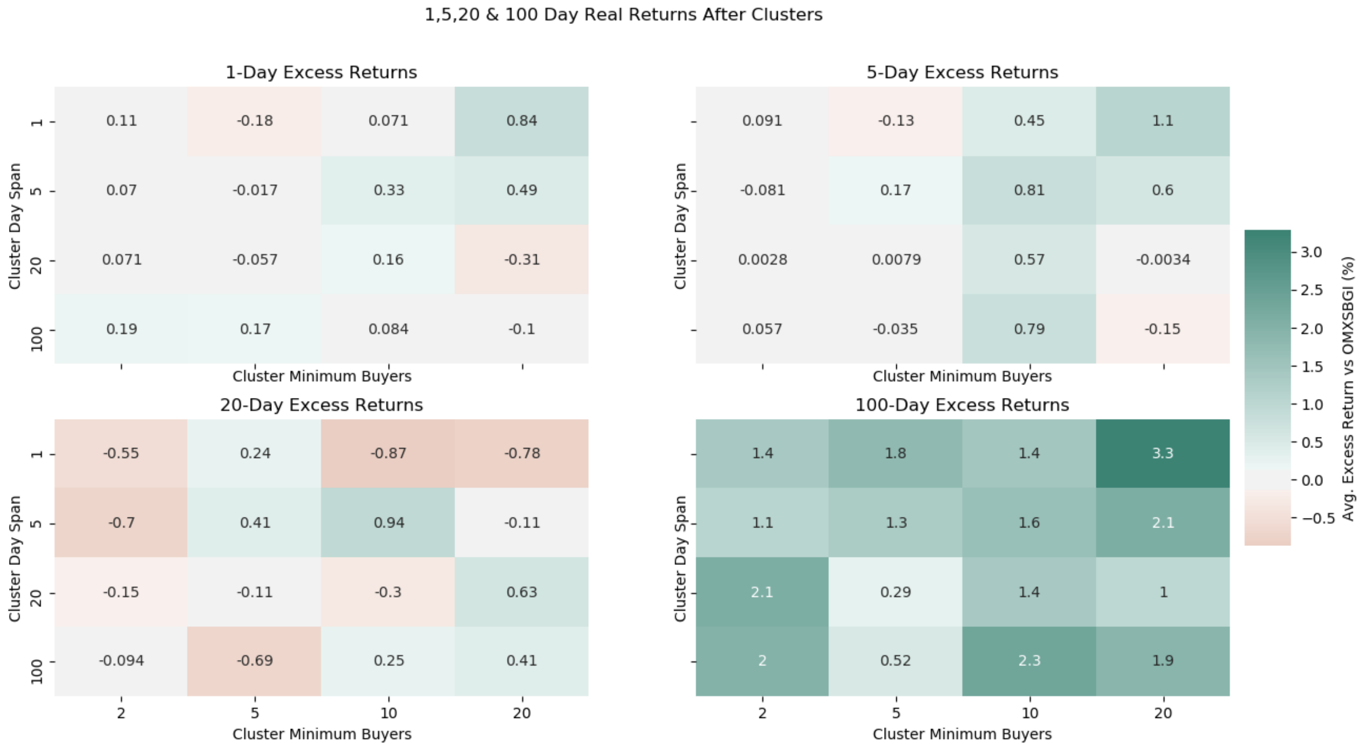

Figure 15: Heatmaps of average excess percentage returns (avg. of trade return - OMXSBGI return) in 1-, 5-, 20- and 100-day holding periods of long positions after insider acquisition clusters combinations, with no other filters (Cluster filter)

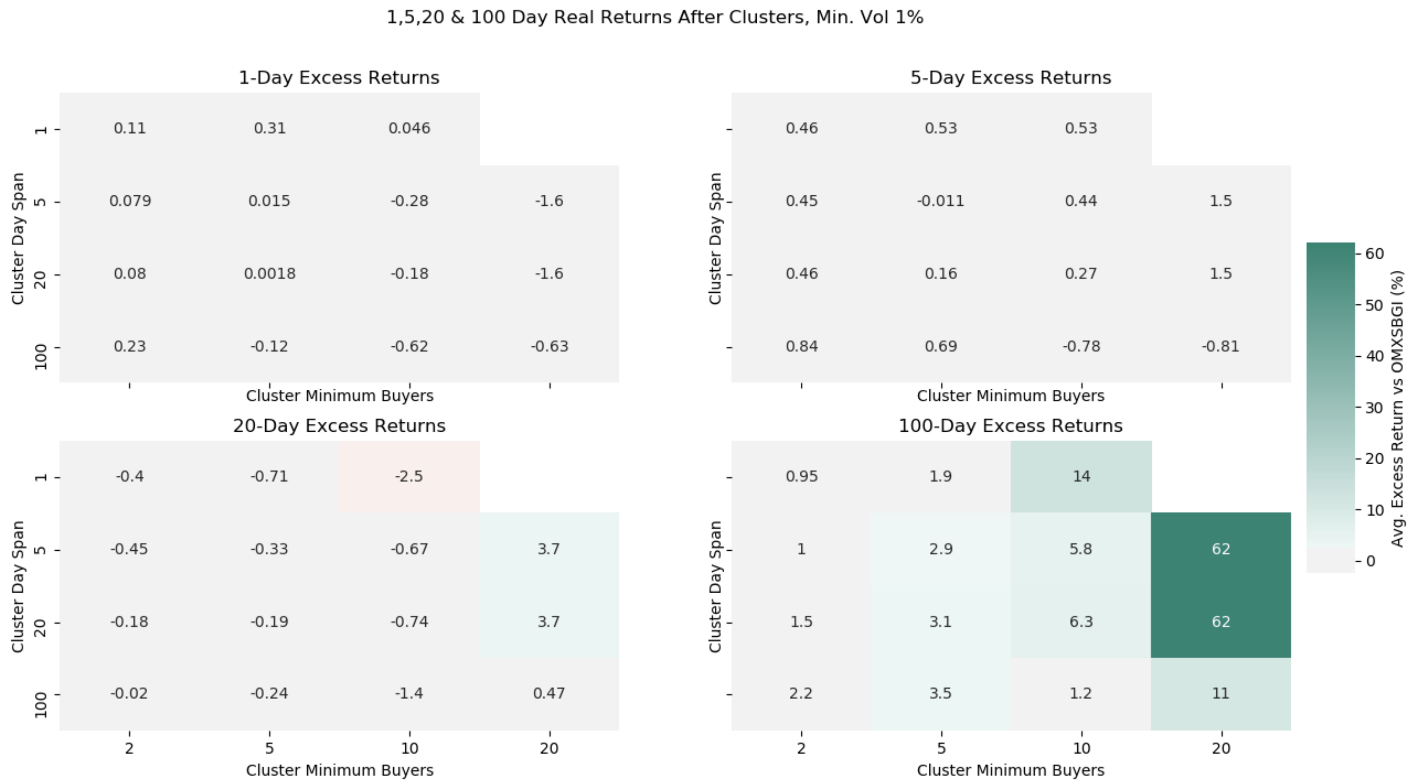

Figure 16: Heatmaps of average excess percentage returns (avg. of trade return - OMXSBGI return) in 1-, 5-, 20- and 100-day holding periods of long positions after insider acquisition clusters combinations, and only acquisitions >1% of daily volume considered (Cluster & volume filter)

Appendix

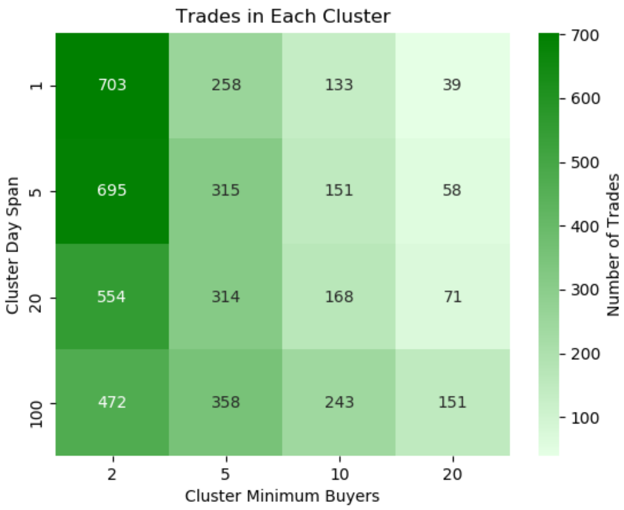

Figure 17: Number of trades after insider acquisition clusters combinations, with no other filters

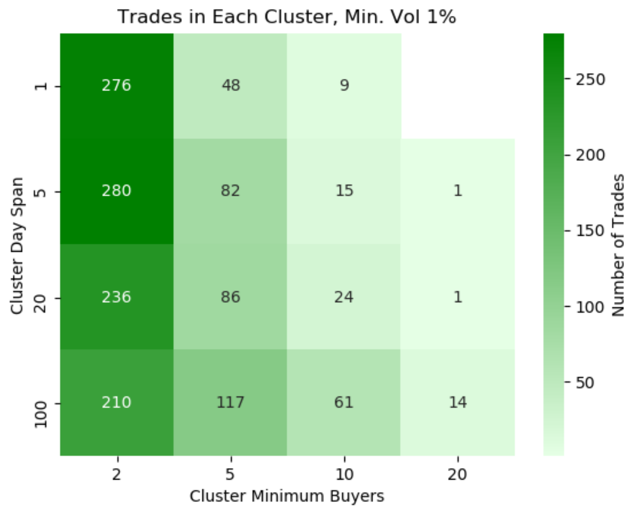

Figure 18: Number of trades after insider acquisition clusters combinations, and only acquisitions >1% of daily volume considered

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Other