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The Value of Next Generation Supply Chain Analytics

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RedGraphs Inc. is a provider of premium supply chain data. Based on their information, we form sorted quintile portfolios according to the peers' return momentum, and also to their node centrality metrics. Various long/short trading strategies generate excess returns that are not explained by common risk factors. We conclude that information from peer companies up and down the supply chain is priced by the market at a delay, which generates profitable trading opportunities. Therefore, accurate knowledge of the economic network is a crucial medium for trading higher degree information.

Introduction

If American Airlines (*AAL*) reports an unforeseen drop in its number of passengers, market participants update their expectations for AAL's future profitability. If the downturn turns out to be persistent, AAL is likely to order fewer jets in the time coming. To formulate that in a probabilistic way, we could say that the likelihood of a decreased jet order in the future has increased as a result of the fewer air traffic passengers today.

Of course, this will subsequently put pressure on Boeing (*BA*), the main supplier of AAL's planes. Further up the supply chain, Kaiser Aluminum (*KALU*) is likely to be affected, too.

It is no novelty that economic actors are heavily interconnected. A shock (positive or negative) in one company's business will be felt by its suppliers and customers. Knowing the supply chain allows investors to trace back the inter-company spillover effects.

In general, sector analysts are well aware of the 1st degree of outward connections, i.e. they know about a company's direct customers. In contrast, direct supplier information for a company may be unknown to the public, although the suppliers may often disclose the company as one of its customers. 2nd-degree relations might only be partially known or considered, while higher-degree ones are likely to be ignored altogether.

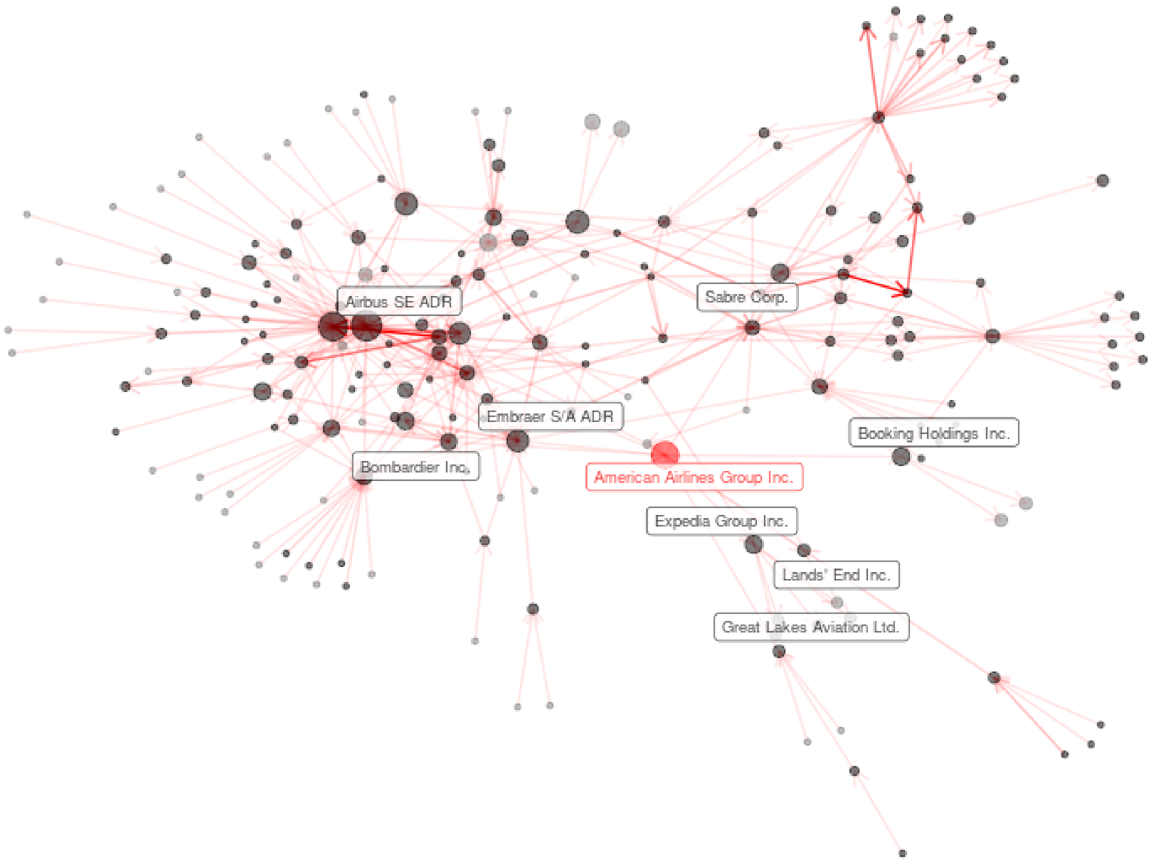

Figure 1: Network of AAL, up to the 3rd degree, as of June 2020

Supply chain information of public companies generally comes incomplete and unstructured. An external collaboration might be mentioned once in a report or on an investor call, yet not be released in the official customers and suppliers list. While many relations stay unknown, US-listed companies are required to disclose their major customers in their 10-K reporting.[1] Sometimes additional information is provided at the

[1] *Regulation S-K334 and U.S. GAAP335 both require disclosures about major customers. (…) Regulation S-K requires disclosure if loss of a customer, or a few customers, would have a material adverse effect on a segment. (…) U.S. GAAP requires disclosure of each customer that comprises 10 percent or more of total revenue.*, see SEC Disclosure Update and Simplification, Section III.D.3. available on https://www.sec.gov/rules/final/2018/33-10532.pdf

discretion of the filing company, as well. Collecting and structuring this disparate information allows us to build a network of companies' economic connections that can be used for analysis.

In the parts that follow, we assess the value in (structured) supply chain data for investors. We do so by building sorted quintile portfolios using metrics from the company's customers or suppliers. The long/short (*L/S*) strategies are formed on an equal-weighted basis with a short leg of stocks from the first quintile and a long leg of stocks from the fifth quintile portfolio.

Method and Data

We look at three categories of sorting approaches as suggested by Zhao et al. (2015).

First, we look at what has been called **return momentum** strategies. Those suggest that the stock performance of related companies (customers or suppliers) to some extent forecasts the performance of a target company's stock. It assumes that the information efficiency on company-specific news is higher for the company itself and lower for related companies. For example, if a company reports lower revenues, this is expected to be immediately priced into their stock with high information efficiency. However, it might take a moment for the related companies' stocks to react accordingly.

Return momentum strategies look for momentum signals from the peers' stock performance. The strategy seeks to capitalize on the information that is already priced in one company but ignored or only partially included in the prices of its customers or suppliers, or the customers of the customers, or suppliers of the suppliers.

Second, we focus on companies' fundamental metrics instead, namely the gross margin of sales. These are called **fundamental flow factor** strategies. The gross margin is predestined for such an approach because of its direct involvement as a measure of supply and demand. Customers and suppliers are constantly attempting to rebalance the profit margins in the supply chain in their own favor. This is the root cause of many supply chain dynamics: pricing actions, new customer segments, mergers & acquisitions, spin-offs, etc. However, these actions take time to implement and view the response, which gives adequate time for trading strategies based on gross margin propagation to be effective.

Third, **link interaction factor** strategies seek to find trading profits based on features directly induced from the number of suppliers or customers or from the supply chain network as a whole. The general idea is that a company with more customers and suppliers, or a company that is more prominently connected to others, is more diversified and independently profitable than a company whose revenue is largely dependent on a few large customers. Serving a single customer will amplify that customer's pricing power over the supplier, which for the target company is likely to lead to smaller profit margins. Simultaneously, if that single customer is idiosyncratically facing a rougher course of business, the supplier might be less flexible to generate its revenue from others, for which it must first establish new channels of sale. We can measure these effects cumulatively by examining the eigenvectors (i.e., axes of profit accumulation) and how their level or change predicts future returns.

For portfolio construction, the general approach followed in this paper is to form sorted quintiles based on signals deviated from the aforementioned strategies. That is, for each point in time *t*, we compute a signal for each company *c* available in the dataset.

As an example, for a return momentum strategy, this would mean looking at the mean stock performance of all of the customers of every company in time *t - 1* (we use the 1-month, 6-month, and 12-month lagged cumulative stock performance). This computed figure is the signal that we store in a *(t, r)* matrix. For each time t (each row) we sort the stocks according to the signal small to large and allocate them to five quantiles.

Subsequently, we compute the return series of each of the five portfolios in which the stocks are equally weighted. Ideally, the sorting leads to visible differences and steadily increasing performance figures (average return or Sharpe ratio) between the quintile portfolios, i.e. the (risk-adjusted) return of the first quintile portfolio is smaller than the second, which is smaller than the third, etc.[2]

For the evaluation, the performance of an L/S portfolio is calculated as the return difference between the fifth and the first quintile portfolios. To assess the profitability, we focus on the Sharpe ratio (SR), the CAPM alpha, and also testing against common risk factors (Size/Value/Momentum).

The following data has been used:

- The main supply chain dataset was provided by RedGraphs Inc., a company that extracts supply chain information from various sources using a state-of-the-art machine learning approach (i.e. natural language processing, NLP). They provide structured data with minimal delay after publication. An example of the main fields used can be found in Table 1. We use data covering a full four-year span from 2015 to 2020. For the following analysis, we exclude financial companies and REITs (SIC range 6021 to 6799) from the portfolio creation but keep their signals for companies of other industries.

[2] rPF1<rPF2<rPF3<rPF4<rPF5

Table 1: Sample data (RedGraphs Inc.)

DT	CUSTOMER_NAME	SUPPLIER_NAME	VALUE	_
2020-06-30	Boeing Co.	General Electric Co.	8 845 200 400	...
2020-06-30	United Parcel Service Inc.	Boeing Co.	7 055 000 600	...
2020-06-30	FedEx Corp.	Boeing Co.	7 055 000 600	...
2020-06-30	Textron Inc.	Boeing Co.	5 142 633 500	...
2020-06-30	Rockwell Collins Inc.	Boeing Co.	2 701 223 170	...

- Stock returns are calculated from adjusted daily closing prices gathered from Sharadar (Nasdaq Data Link). We exclude penny stocks if their closing price is $0.01 or below.

Results

Return momentum

In return momentum strategies we look first at customers' and then at suppliers' past stock performance. The notion of looking at customers is straightforward: a company should be doing well if its customers are doing well (which should be reflected in an increase in everyone's market valuation). One step up the supply chain, the suppliers of that one company should also be doing well.

The same mechanism for suppliers is a bit less intuitive (i.e. a company's stock is doing well if its suppliers are doing well), but could reflect suppliers providing better goods and services to their customers that improve the customers' productivity (or inversely dropping goods or services that require replacement). For it to work, the stock of a customer of company should rise after the rise of the stock of its supplier. As reported in the following, we find clear patterns in both directions.

Figure 1 shows the annualized returns of five quantile portfolios sorted on the direct customers' past 12-month stock return (not excluding the very last month, as studies on the conventional momentum factor often do). While the 1st quantile (the ones with the lowest peers' returns), delivered the lowest return on average, the top quantile outperformed. This results in a positive performing L/S portfolio.

Figure 1: Annualized returns of portfolios sorted on the 1st-degree suppliers' prior 12-month stock return.

The L/S portfolios (5th quantile minus 1st quantile) on both 1st-degree suppliers and 1st-degree customers for 6- and 12-month periods delivered positive risk-adjusted returns (Sharpe ratios between 0.57 and 1.06). The CAPM alpha is highly significant for all variants. While all of them have strong loadings on the momentum factor, the significant alpha persists even when controlled for size, value, and momentum (Carhart 4-factor model), see Table 2.

Table 2: 1st degree return momentum strategies (*p<0.1, **p<0.05, ***p<0.01)

Metric	**SR**	**CAPM alpha (annualized)**	**Carhart 4-factor alpha (ann.)**
1st degree suppliers past 6m return	1.06	14.58% ***	11.08% ***
1st degree customers past 6m return	0.90	14.85% ***	10.19% ***
1st degree suppliers past 12m return	0.57	7.91% ***	4.47% *
1st degree customers past 12m return	0.98	9.30% ***	7.56% ***

The fact that alpha persists even when controlled for the momentum factor shows that performance is not driven by systematic market momentum. The loadings on the size factor are insignificant in all of these L/S portfolios.

For both directions, the 6-month past return leads to better results compared to the 12-month past return. A shorter period (1 month) does not lead to exceptional returns and nor does the opposite (mean reversal).

The displayed results are for the equal-weighted portfolios, but the value-weighted results do not differ much.

Looking at second-degree relationships, we find mixed results, see Table 3. The L/S strategies over 6 months perform relatively well, however, the alpha turns insignificant when controlled for other factors.

Table 3: Second-degree return momentum strategies

Metric	**SR**	**CAPM alpha (annualized)**	**Carhart 4-factor alpha (ann.)**
1st-degree suppliers past 6m return	0.63	8.09% ***	5.81%
1st-degree customers past 6m return	0.76	7.39% ***	5.34%
1st degree suppliers past 12m return	0.07	-0.33%	-1.52%
1st degree customers past 12m return	0.61	3.59%	4.25%

Information is quickly priced in, whereas it takes some time to spread to other companies up the supply chain as analysts slowly incorporate the information. A company's value is influenced clearly by idiosyncratic moves on both its suppliers' and customers' stock prices.

We imagine that the second (and further) degree information becomes more relevant to generate excess returns when using supply chain data becomes more widespread. Our strategies using the second-degree momentum signal could be optimized using a weighted signal according to the share of revenue (for customers) or share of cost (for suppliers).

One possible explanation for our signals' performance is that smaller capitalization stocks are generally covered by fewer analysts. Therefore, one might expect that those stocks exhibit higher market inefficiencies and would be more profitable in a supply chain momentum strategy. To evaluate such patterns, we form conditional double-sorted portfolios, i.e. first sorting the equities according to their market capitalization (where we use three quantiles low/medium/high), and second sorting for the momentum signal as before.

Contrary to the hypothesis, we do not find better but more unstable performances with small-caps. This indicates that profound knowledge of the supply chain is relevant for all company sizes, small to large. In general, the large-cap (top ⅓) subset shows a clearer pattern in quantile portfolio returns. This can be seen in Figure 2 compared to Figure 3.

Figure 2: Annualized returns of portfolios sorted on the 1st-degree customers' prior 6-month stock return, small caps (lowest ⅓ market capitalization)

Figure 3: Annualized returns of portfolios sorted on the 1st-degree customers' prior 6-month stock return, large caps (highest ⅓ market capitalization)

We reason that while large caps are more covered by analysts, those do not necessarily take into account the elevated complexity of those companies' supply chain connections. This bodes well for the long-term success of a supply chain trading strategy.

Fundamental flow factors

Using the related companies' recently reported fundamentals (or especially also the change in fundamentals) is a seemingly appealing approach to forming portfolios. The one metric that we focus on is the gross profit margin.

One can take two approaches for this, either to use the absolute peer average of the fundamental metric as the signal, or the change of it over time.

Table 4: First-degree fundamental flow strategies

Metric	**SR**	**CAPM alpha (annualized)**	**Carhart 4-factor alpha (ann.)**
1st-degree suppliers gross profit margin	0.32	12.14%	3.74%
1st-degree customers gross profit margin	0.70	11.56% ***	3.69%
Change in 1st-degree suppliers gross profit margin	0.10	1.48%	-0.28%
Change in 1st-degree customers gross profit margin	0.47	0.95%	0.48%

While all of the L/S portfolios formed on gross margin had positive returns, the one on customer gross margin exceeded the one on supplier gross margin. This makes sense as the customer side is a natural way that value is added. Higher margins are a sign of greater pricing power which positively influences the profitability of suppliers of these companies.

While the CAPM alphas for the absolute gross profit margins are stable, it decays in the Carhart 4-factor model. The reason is a strong negative loading on the size factor. This is due to the overlap of large corporations with pricing power which leads to greater margins.

Interaction factors

We initially use the mere number of first degrees inward, outward, or total, as signals. Their result in an L/S strategy setup is inconclusive. While similarly to Zhao et al. (2015), some degree ratios (e.g. number of degrees divided by market capitalization) might deliver better results, such signals are seemingly heavily synthesized (*data dredging*).

To incorporate graph characteristics beyond the first degree, we have to look at centrality measures. A centrality gives a score of importance to each node in a network. While several centralities have been proposed, the most common ones are provided by RedGraphs Inc. These are (besides the degree centrality): closeness, betweenness, and eigenvector centrality. The latter can be thought of as following money flow in the world economy and assigning a higher score the more times it passes by one entity.

One can expect to find better performances in companies with higher centrality scores. The more important or interconnected a company is, the better its stock does.

We first look at the performance of an L/S portfolio built on sortings according to the absolute centrality scores, see Table 5.

Table 5: Graph centrality measurements strategies

Metric	**SR**	**CAPM alpha (annualized)**	**Carhart 4-factor alpha (ann.)**
Degree centrality out (customers)	0.55	9.01%	1.71%
Degree centrality in (suppliers)	-0.28	-3.42%	-4.13%
Weight out (customers)	0.38	-6.52% ***	-6.34% ***
Weight in (suppliers)	-0.51	-17.38% ***	-13.05% ***
Closeness centrality	0.42	4.51%	-1.76%
Betweenness centrality	0.23	-0.03%	-3.24%
Eigenvector centrality suppliers	0.59	-2.09%	0.67%
Eigenvector centrality customers	0.40	-6.95% **	-6.51% **

The L/S portfolios on degree centrality out (that is the absolute count of customers) and the weight out (the dollar worth of the customer connections) result in positive returns. Having a higher number of customers makes companies less dependent on a few and strengthens their performance.

A higher number of suppliers (or weight in) does poorly in an L/S strategy. The negative impact of depending on more suppliers and having a higher money outflow makes sense because more of the company's potential profit is being sent to its suppliers.

The same L/S strategy on the closeness centrality and betweenness centrality led to positive Sharpe ratios. Closeness measures the level of a company's integration into the broader economy and can be used as a proxy for economic health. In the alphas, we obtain mixed results. The reason is the high explanation of the returns by the market return (beta) and size.

The same holds true for the eigenvector centralities. While these led to higher risk-adjusted returns, these are explained by common factors. Larger firms have more connections and therefore rank higher on all unadjusted centrality measurements, especially the eigenvector centrality.

The solution is to adjust the values by the market capitalization, however, for the 6-year span of the available data, we do not observe excess returns on the mentioned centrality measurements. While we strongly believe that one should observe alpha in the absolute eigenvector centralities (and the others), this is just not present in the evaluated period. In our defense, one has to remember that over the same timespan, Fama-French's size (SMB) and value (HML) premium were negative as well. One possible explanation could be that we are reaching a peak in market consolidation (oligopolies, monopolies, monopsonies, etc.) and there are reduced benefits to size once a company has already reached the maximum.

We further look at the month-to-month changes in the metrics. The idea is that those companies that gain new customers or suppliers and improve their overall importance in the network should do better, see Table 6.

As expected, we find positive returns and a significant alpha for the change in the degree out and in. Companies that recently reported new additional connections (i.e. new customers or suppliers) outperformed. Similar good returns are achieved with weight out and in.

An improvement in closeness centrality led to higher returns. On the other hand, improving on the betweenness score resulted in hurt stock performance. Betweenness is a measure of a company being a bottleneck, and would not drive returns, possibly because other companies impacted by a significant bottleneck are beginning to diversify away from the associated risk.

As one could expect, the change in eigenvector centralities had a positive impact on the stock.

Table 6: Graph centrality measurement changes strategies

Metric	SR	CAPM alpha (annualized)	Carhart 4-factor alpha (ann.)
Change in degree centrality out (customers)	0.37	8.06% ***	7.78% ***
Change in-degree centrality in (suppliers)	0.49	7.52% ***	7.20% ***
Change in weight out (customers)	0.16	-2.43%	-6.00%
Change in weight in (suppliers)	0.44	4.19%	2.36%
Change in closeness centrality	0.55	3.76%	1.32%
Change in betweenness centrality	-0.41	-6.43%	-5.14%
Change in eigenvector centrality suppliers	0.32	1.13%	2.04%
Change in eigenvector centrality customers	0.32	10.20%	5.43%

Conclusion

In this paper, we have constructed a variety of portfolios based on supply chain data metrics. While some of the L/S portfolios achieved exceptional performance for the time window evaluated, some strategies do not lead to the same level of results. In general, the strategies that make intuitive sense given typical supply chain dynamics and have clear reasoning behind them have worked well. From the analysis, the conclusions are straightforward:

- Investors still appear to focus primarily on customer relationships, as first-degree customer momentum remains a strong factor.
- Supplier momentum is also clearly visible and tends to be incorporated into the market later.
- Changes in profitability metrics, namely the gross profit margin, can push or pull value up and down the supply chain, affecting the future performance of customers and suppliers.
- Complex centrality metrics are not fully incorporated in the market, either statically or dynamically.

Contrary to the results in previous publications (Zhao et al. 2015), we found less significant performance for very simple strategies. We believe that the following points might have also caused the alpha to be different from prior measurements:

- The equity market is selectively efficient based on what investors are considering at the moment. Some simple signals quickly become incorporated, but others can languish because analysts have limited capacity. Supply chain data appears to be in a mixed state that is mostly unincorporated until it becomes overwhelming.
- Refinements of the strategies may be needed to fully replicate the measured alpha, such as filters for recent volatility that could prevent binning a stock in the improper quantile, higher frequency fundamental data to capture recent changes or adjustments for expectations and surprises in forecasts.
- Coverage differences undoubtedly exist between the RedGraphs and the data used in previous publications because of the reporting time period and the sources used, which could easily drive measurement differences.

Notably, the strategies presented in this paper are relatively simple. While many of them are profitable in our backtests, we are aware that this is insufficient for a trader to start replicating as-is. The number of stocks in both the long and the short leg, as well as the monthly turnover, need to be considered appropriate for the investor's risk and trading tolerances.

Regardless, the main goal was to show that even relatively straightforward signals from timely supply chain data contain robust alpha, and that is the case across a variety of strategy types.

Disclaimer

References

Bonacich, Phillip, and Paulette Lloyd. 2001. "Eigenvector-Like Measures of Centrality for Asymmetric Relations." *Social Networks* 23 (3). Elsevier: 191–201.

Fama, Eugene F. 1991. "Efficient Capital Markets: II." *The Journal of Finance* 46 (5). Wiley Online Library: 1575–1617.

Zhao, George, Kevin Webster, CFA Yin Luo, Sheng Wang, David Elledge, Miguel-A Alvarez, and Allen Wang. 2015. "The Logistics of Supply Chain Alpha." *Deutsche Bank Market Research*.