ABNORMAL STOCK RETURNS USING SUPPLY CHAIN MOMENTUM AND OPERATIONAL FINANCIALS

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ABSTRACT

Knowledge about a company’s supply chain provides an edge for investors. In this new proposed trading approach, a company’s stock is only purchased if its main customer’s quarterly sales evolve favourably. This method yields backtested annual returns in excess of 10.1% to the market return net of transaction costs over a 12 years period for a stock portfolio built on supply chain considerations. This portfolio is uncorrelated to the market and the abnormal return is robust for risk-adjustment. The method is at least applicable for U.S. listed product manufacturing small and mid-capitalisations with a strong dependency on their main customer company. A review of past publications finds no description of this method, thereby confirming the novelty of this hard facts approach.

A supply chain or supply network is a multi-company material flow ecosystem surrounding a production company. Stock price or operational data of *customer* companies provides an indication of *supplier* company future operations and business performance. The delays and time lags between supply chain operations may give an opportunity to forecast company performance even before the company publishes its own financial reports. Understanding the interrelationships between supply chain partners' businesses intuitively provides an opportunity to gain abnormal investment returns in the stock market.

Although several studies have been accomplished upon supply chain implications for shareholder wealth, the majority of related research focuses on single companies instead of supply chains, on company financial performance instead of stock market performance and on special events analysis instead of studying continuous operations. Further variations include emphasis on either upstream or downstream sides of the supply chain, the size of the sector studied and the variety of sampled companies within the submarket.

One of the first supply chain stock price prediction studies claimed abnormal returns on investment using customer company market prices to predict the supplier companies' stock returns. A later study claims these abnormal returns have almost disappeared. The latter finding is in line with the theory of efficient markets. We explore further opportunities for customer related information by switching to a completely different data set - using financial reporting data instead of stock market data to improve supplier company stock returns. Leaving the customer company stock price out of the forecasting method results implies that some important qualitative market factors like management predictions for the future, competitive situation, new products in the business pipeline and dividend policies are being ignored. We, however, think that these very different perspectives should be kept separate at first and be integrated to a single forecasting method in future research.

This paper studies such supplier-customer supply chain pairs, where the business link is strong and has existed for a longer period. This ensures high quality data and validity across business cycles, but also limits the size of the sample. Because of the nature of the supply chains, most supplier companies are essentially smaller than their customer companies and can in most cases be regarded as mid-cap or small-cap companies (by U.S. market perceptions).

One of the key ideas of this study is to exploit more fundamental data than stock prices - operational supply chain related financial data derived from 10-Q quarterly reports (for Q1-Q3) and annual 10-K reports (for Q4) in predicting supplier stock prices. This approach opens a new perspective in supplier stock price prediction, by omitting stock price related speculation, under/overreactions and altering market expectations for stock prices by (un)sophisticated investors.

While investment practitioners already follow supply chains of large cap companies, the same amount of analyst man-power is not cost-effective applied to mid-cap or small-cap companies. For the smaller companies, availability of company specific information also becomes a challenge. This is why we propose a portfolio rebalancing/trading solution with minimal subjective influence applying publicly available company reporting data.

SUPPLY CHAIN KNOWLEDGE ASSISTED STOCK TRADING SO FAR

To date, many authors have investigated the links between supply chains and the stock market, suggesting the existence of trading strategies producing abnormal returns. Cohen and Frazzini [2008] were among the first, claiming abnormal annual returns of 18.6% by using the performance of customer companies as a predictor of the supplier companies' performance. They found a time-lag between the market performance of a customer company and its suppliers. The performance of all the customer companies' stocks of the previous month is organised in five quintiles according to stock price increase. The stocks of the corresponding suppliers are purchased (shorted) in the following month for all customer companies in the top (bottom) quintile. This source of abnormal return and predictability is referred to as *customer momentum* throughout this paper.

The above mentioned study spans from 1980 to 2004 and focuses on companies listed in the U.S. with share prices above $5 and is restricted to companies having a single customer generating 10% or more of total sales. These findings of customer momentum for the U.S. market are confirmed by a second study [Shahrur et al. 2009], which investigates a sample of firms from 22 developed markets from 1995 to 2007. Since the probed markets do not necessarily require companies to disclose their main customers, the authors ranked portfolios of supplier companies (e.g., car part suppliers) based on returns of customer companies (e.g., car makers). The lead-lag effect found was more pronounced for small suppliers and for supplier industries with dispersed sales and with higher relationship-specific investments with their customers. Buying supplier industries with the highest customer returns after a 1 month time-lag in the top quintile and selling short the industries with the lowest customer returns in the bottom quintile yields annually up to 15% of abnormal return.

Investor inattention or the failure of many investors to include relevant information from a company's supply chain is advanced by Cohen and Frazzini [2008] as a possible explanation for the stated abnormal returns. Merton's model [Merton 1987] offers some explanation for investor inattention, where investors supposedly evaluate whether the gains of a new strategy are worth the total cost of implementing and operating it, including time and resources to market the strategy to clients and legal compliance. If the perceived total cost is prohibitively high, its elimination by the market can amount to several years.

Six years after the initial publication by Cohen and Frazzini [2008], another study by Wu and Birge [2014] claims that customer momentum has almost completely disappeared and suggests two new approaches yielding abnormal returns. One is *supplier momentum*, that is, inverting the roles of customer and supplier in the above described trading strategy. The other approach, called *centrality*, consists of assessing the interaction strength of a company within its network. By doing so, abnormally low returns are expected for highly networked manufacturing companies, whereas abnormally high returns are typical for more central companies like in transportation, wholesale and retail sectors.

Guan et al. [2011] claim that the improvement in forecasting accuracy reached by customer momentum is statistically as significant as in following industry peers of the analysed supplier company.

The effects of supply chain disruptions have also been studied. The authors in [Hendricks and Singhal 2003] state that supply chain glitch announcements are associated with an abnormal decrease in shareholder value of 10% and that larger firms or firms with lower growth prospects experience a less negative market reaction. The monthly sales announcements of firms in the retail industry seemingly affect their suppliers' stock price [Olsen and Dietrich 1985]. In a study focused on a single manufacturing company (1980-2005), a correlation between inventory performance and profit is reported [Capkun and Hameri 2009]. Commodities with global market prices can also be thought to have a "supplier" role for some companies. A decrease in oil price one month on average indicates a higher stock market return the following month. Backtesting concludes that this strategy yields an abnormal annual return of +4% after transaction costs over several years [Driesprong et al. 2003].

None of the publications to date did directly link the operational financials – for example sales or inventories – of a customer company to predict the share price of its suppliers. The absence of such a published forecasting procedure based on operational financials is what motivated our exploration of a new trading method.

As is the case for any trading method, the lack of a publication is by no means proof that the method is not used. However it suggests that such a strategy is in its infancy or not published for competitive reasons.

ANATOMY OF THE PROPOSED TRADING METHODOLOGY

Both balance sheet and income statement related variables were considered for the proposed trading method. These variables – referred to as *supply chain financials* (SCF) in the following – were all included as input data candidates for price prediction method issuing trading recommendations:

- Net sales
- Cost of goods sold
- Inventories
- Inventory turnover (Sales/Inventories)
- Accounts payable
- Accounts receivable.

The suitability of the listed variables to predict share price movements was assessed by testing each of the listed variables individually as an input for a trading method issuing buying and selling recommendations for the supplier company's shares. The principal logic of the trading method is the same as used in earlier work [Cohen and Frazzini 2008], except that the input variables were changed and timing parameters (when to buy and sell) were optimised anew. Naturally, the sampling frequency cannot be optimised. It is fixed to four times a year due the quarterly reporting rhythm. After reception of new quarterly reporting data, the trading method performs comparisons of customer company SCF variables in the previous quarter. Depending on this comparison outcome, a recommendation to buy the stock of the corresponding supplier company is issued and the resulting return on investment is computed. A more technical description of the method is found in the Endnotes.

Since there are no standardised criteria to select the best suited input variables, we opted for a procedure maximising the method's utility from an investor's point of view under realistic trading conditions. We therefore chose the Sortino ratio [Sortino and Price 1994] as the output variable, since maximising the Sortino ratio ensures an optimal balance between risk and return. The Sortino ratio seems better suited than the more widely used Sharpe ratio since the former distinguishes between upside and downside volatility in agreement with most investors, who welcome large positive returns.

All studied customer – supplier company pairs were selected based on the methodology described in [Cohen and Frazzini 2008], where the pair selection was done by exclusively considering companies which disclose sales to a single customer of over 10% of the total sales. For meaningful backtesting only company pairs fulfilling this 10% sales threshold for at least seven years were retained. In order to facilitate a possible practical implementation of the method, only publicly available data was considered. This restricts the pool of suitable companies to the U.S. stock market. The S.E.C. has been requiring listed companies to disclose such information since 1998. The share prices used in the calculation are the daily adjusted closing prices. An effective transaction cost of 0.1% of the traded assets was assumed for every trade consisting of buying and selling a share. The impact of total transaction costs on the results is discussed later. Information was solely retrieved from the Morningstar website since the reports are available there on the very day they are officially published. This constraint practically sets the beginning of the backtesting period to January 2002 for the majority of the selected companies. Prior to 2002, only a minority of financial reports can be retrieved electronically from this service. At the other end, data was collected until December 2013, the latest full year considered for this study. This timeframe of twelve years is long enough to test the methodology over various regimes of economic growth and abrupt contraction in 2008 – 2009 for the U.S. economy.

Company selection began with a set of over 200 randomly chosen small and mid-size market capitalisation companies within the U.S. market from different industries with broadly varying product lifecycles and manufacturing lead times. In these selected supply chain company pairs, the supplier companies are typically smaller than the customer company. Small supplier companies are more likely to form longer lasting bonds with a customer fulfilling the 10% sales threshold. The focus was set on companies mainly producing tangible products. Companies from the financial and insurance sectors, for example, were not considered.

After applying these various constraints the original company set was narrowed to 20 companies forming ten company-pairs. An initially balanced portfolio consisting of shares for these ten supplier companies grew at a pace compatible with the Russell2000 index over the studied time period of twelve years, making this company set a representative sample of U.S. based goods manufacturing suppliers to test our trading method. The twenty companies involved are listed in Exhibit 1. The proposed investment strategy was validated by studying the returns of a heterogeneous portfolio of ten companies. Although the companies were dissimilar in the business sense, they shared the strictest requirements for data quality for the entire study period. The sales percentages in Exhibit 1 represent the average share of total sales attributable to the corresponding customer company over the studied period. One of the supplier companies (Spirit Aerosystems) is of particular interest and referred to as the high dependence supplier in the following.

Supplier Co.	Ticker	Customer Co.	Ticker	Sales (% total sales)
Standard Motor Products	SMP	Advance Auto Parts	AAP	15%
Oil-Dri. Co.	ODC	Clorox	CLX	10%
Spirit Aerosystems	SPR	Boeing	BA	90%
NL Industries	NL	Harley Davidson	HOG	15%
CompX International Inc	CIX	Harley Davidson	HOG	10%
Par Technologies	PAR	Yum Brands	YUM	35%
Lydall	LDL	Ford	F	15%
Material Sciences	MASC	Ford	F	20%
ZEP Inc	ZEP	Home Depot	HD	10%
The Scotts Miracle-Gro Company	SMG	Home Depot	HD	30%

Exhibit 1: List of the ten studied supplier – customer company pairs and the share of sales attributable to the customer company with respect to the total supplier company's sales.

THE PREDICTIVE POWER OF SUPPLY CHAIN "HARD" KNOWLEDGE

The first part of the analysis consisted of selecting SCF variables and optimising the timing parameters of the trading method. The Sortino ratios computed based on the trading recommendations for each of the SCF are listed in Exhibit 2 below. The Sortino ratios for applying each variable are compared against returns of two indexes, the S&P500 and Russell2000 plus the passive buy & hold strategy using the subset of companies listed in Exhibit 1. Passive returns result from buying shares of the supplier company at the earliest possible date (January 2002 or the day the supplier company was publicly listed) and holding them until the end of the period (December 2013). The Passive portfolio is included in the analysis to assess the potential sampling bias. The quoted Sortino ratios for the various SCF variables are computed for the high dependence supplier stock since this allows to test the predictive power of the method under almost ideal conditions of a very strong customer-supplier link.

Inputs from customer company	**Sortino Ratio**
Sales	1.55
Cost of goods sold (COGS)	1.48
Inventories (INV)	0.49
Sales/Inventories (Sales/INV)	0.77
Accounts receivable (A/R)	0.40
Accounts payable (A/P)	0.63

Selected reference Sortino ratios for comparison	**Sortino Ratio**
Passive	0.19
S&P500	0.19
Russell2000	0.21

Exhibit 2: Sortino ratios for various input SCF variables of the trading methodology. Sortino ratios of two market indexes and a passive buy & hold strategy are also displayed for comparison purposes.

The variable *Sales* of the customer company is the best suited input SCF for the trading method due to its highest scoring Sortino ratio. The tests show that the variable COGS provides only slightly lesser returns. This is also intuitively understandable since sales and COGS are closely related in efficiently managed companies. Unlike anticipated, using downstream inventory data did not show strong improvements in the Sortino ratio.

Having identified the optimal SCF, backtesting was extended to include a portfolio of the supplier companies listed in Exhibit 1. The backtested individual compound annual growth rates for the ten companies and for an initially equally weighted portfolio of these companies obtained from active and passive trading are displayed in Exhibit 3. The assumed effective transaction cost is 0.1% of the traded assets.

	CAGR Active	CAGR Passive	ΔCAGR Act. - Pas.
SMP	26.9%	11.3%	15.6%
ODC	20.9%	19.9%	1.0%
SPR	21.5%	2.2%	19.3%
NL	24.3%	9.8%	14.5%
CIX	11.6%	4.6%	7.0%
PAR	16.5%	9.9%	6.6%
ZEP	6.6%	5.4%	1.2%
MASC	15.6%	1.4%	14.2%
LDL	12.6%	4.5%	8.1%
SMG	6.8%	11.1%	-4.4%

	All 10 Active	All 10 Passive	S&P500	Rus2000
CAGR	**17.5%**	**9.4%**	**3.9%**	**7.4%**
Sortino	**0.94**	**0.19**	**0.11**	**0.16**

Exhibit 3: Computed compound annual growth rates of the ten individual stocks based on passive and active trading. The key outcomes are the significantly improved CAGR and Sortino ratios in the Active portfolio. The CAGR and Sortino ratios of a portfolio for the ten companies with initial equal weight and two market indexes are also displayed for comparison purposes.

The active portfolio beats the S&P500 and Russell2000 indexes annually by 13.6% and 10.1% respectively. More importantly for some investors, the risk-adjusted Sortino-ratios are over five times better than for the Russell2000 reference index. For nine out of ten companies, the active portfolio beats the passive portfolio. For one company stock (SMG), the passive investment exceptionally yields better returns. This result is discussed later in the text. The Sortino ratio of the Passive portfolio is comparable to the market indexes, meaning that after adjusting for risk, there is no significant selection bias of the company sample.

An appealing feature of the active portfolio is that it is materially uncorrelated with the broader market: correlations are -0.14 for Russell2000 and -0.18 for S&P500. The standard deviation of the active portfolio monthly returns (see Exhibit 4) is comparable to the S&P500

market index, while the average monthly return of the active portfolio is significantly higher than any of the other three benchmarks. This is an indication that the abnormal returns of the active portfolio are not the result of a few particularly successful single trades.

Correlation of monthly returns 01.2002 - 12.2013

	SP500	Rs2000	Passive	Active
SP500	1.00	0.93	0.69	**-0.18**
Rs2000		1.00	0.78	**-0.14**
Passive			1.00	**-0.11**
Active				1.00

Characteristics of monthly returns 01.2002 - 12.2013

	SP500	Rs2000	Passive	Active
median	1.1%	1.2%	1.3%	0.0%
average	0.4%	0.8%	1.0%	1.4%
std. dev.	4.9%	6.5%	6.9%	4.1%
min.	-16.8%	-22.5%	-17.6%	-9.8%
max.	15.7%	21.3%	25.1%	27.8%

Exhibit 4: (Top) Correlations of the monthly returns between the S&P500, Russell2000, passive and active portfolios. The near zero correlation values between the active portfolio and the three other strategies may be appealing to investors also from a pure diversification point of view. (Bottom) Characteristics of the monthly returns of both indexes and both portfolios.

The key metrics – that is, correlation, monthly returns and compound annual growth rate – of the passive portfolio and the Russell2000 index over the studied period lay within the same range. If the passive portfolio is considered as a proxy for the market index, the difference in the average monthly returns of +0.4% between the active (+1.4%) and passive (+1.0%) portfolios quantifies the abnormal return provided by including information from the supply chain in the stock trading of these companies.

For the studied sample there is no significant correlation between the amount of supplier dependence on its main customer and abnormal returns (see Exhibit 5).

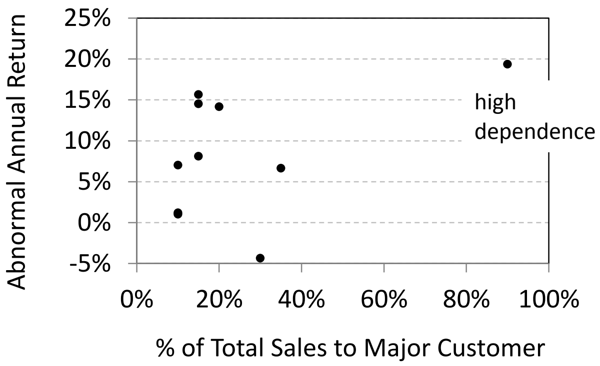


Exhibit 5: Abnormal annual returns defined as the difference in CAGR between the active and passive investment strategies of the ten supplier company stocks as a function of the percentage of total sales to these companies' main customers.

This means that exceptionally large single customer sales are not a prerequisite for high returns. Since it is more likely to find a supplier company with a 10% rather than, for example, a 30% sales dependence on a single customer, this lack of correlation is a useful finding when implementing the trading method in a real environment. It broadens the group of companies for which the stock may be traded.

VALIDITY OF ABNORMAL RETURNS

The calculated abnormal annual returns of at least +10% show that opportunities for exploiting customer momentum still exist, unlike claimed by Wu and Birge [2014], but achieving them requires the use of new data sets. The results are also in line with single-company research, where low inventories also presuppose improved business performance. However the return potential is smaller than shown in the earlier customer momentum research. One obvious reason for this is the smaller number of yearly runs of the method due to only four quarterly predictions per year against 12 predictions in monthly runs.

Given the various backgrounds of the probed companies, there can be no single straightforward cause to explain the abnormal returns. A simple supply chain explanation is that in a long-term partnership, increasing outbound materials flows of a customer company will lead to increased material flows from the suppliers. This will later ignite supplier topline growth, economies of scale and in the majority of cases increased future cash flows and finally, higher valuation of suppliers.

Due to the selection criteria of the mentioned supplier-customer company pairs the reported abnormal returns are likely to apply for the entire subset of U.S. small capitalisations mainly manufacturing goods with at least one large customer.

As noted in past studies [Thomas and Zhang 2002], quarterly sales and inventory figures may be subject to manipulation by company executives. While such distortions can surely not be excluded, the twelve years analysis period mitigates the total effect of temporary anomalies.

The estimate used for the default transaction cost (0.1%) can be challenged. However, in most of the past publications, transaction costs were not considered at all. The accurate estimation of realistic transaction costs is problematic due to the varying spreads of stock prices and because of the variation in trading practices to reduce the effective spread.

The role of luck in generating abnormal returns for the company pair with the strongest bond was ruled out by Monte-Carlo simulations, where results of random buy and sell recommendations were compared against the backtested returns. The simulation results rule out luck with a comfortable safety margin for practitioners. The details of these calculations are presented in the Endnotes.

As noted before, the trading method fails to beat the passive strategy for one company, The Scotts Miracle-Gro Company (SMG), producing branded consumer lawn and garden products of superior quality. A thorough company specific investigation of this underperformance goes beyond the scope of this article. Beyond obvious seasonality issues, reasonable explanations for this behaviour include the fact that SMG has three large customers, Home Depot, Lowe's and Walmart, which together account for 60%-70% of its sales. It could be that the method works less reliably when several, instead of one, customers cross the 10% threshold of total sales.

Companies with small capitalisations typically have a lesser analyst coverage. The abnormal returns may be explained at least partially by a lack of awareness of many investors concerning these links in the supply chain. Although executing the proposed stock trading is neither time-consuming nor difficult, the methodology required for implementation creates a certain entry barrier.

BENEFITTING FROM PRACTICAL IMPLEMENTATION OF SUPPLY CHAIN KNOWLEDGE

Supply chain analysis of a company as a part of asset management has unexplored benefits. The benefits are two-fold. First, the supply chain analysis in addition to single company analysis increases the investment returns. Second, the diversification of the portfolio will improve as shown. However, the successful application of the proposed active portfolio requires informed selection of companies to invest in and thereafter efficient execution of the transactions.

With the quarterly analysis design, the active portfolio involves a relatively high asset turnover ranging typically between 200% and 300% annually. For this reason the transaction costs play a decisive role in return performance. All results presented so far assume effective transaction costs, that is, the effective cost of buying and selling a stock, of 0.1% of the value of the traded assets. Transaction costs may be explicit such as commissions and fees but also implicit such as unusually large bid/ask spreads [Fabozzi et al. 2010]. Whereas explicit costs tend to be independent of the stock, implicit costs typically increase for less traded stock, which is mainly the case for smaller companies.

The annual returns of the active and customer momentum portfolios are plotted in Exhibit 6 for effective transaction costs up to 0.9%. Exhibit 6 shows that the return drops by 0.3% for every 0.1% increase in effective transaction cost for the active portfolio. This drop is significantly steeper for the earlier researched customer momentum strategies. The active portfolio can survive real world transaction costs, whereas the performance of momentum strategy with likely 3-4 times higher turnover is at risk. The new method proposed is much less sensitive for true transaction costs and survives well in the real-world operating environment.

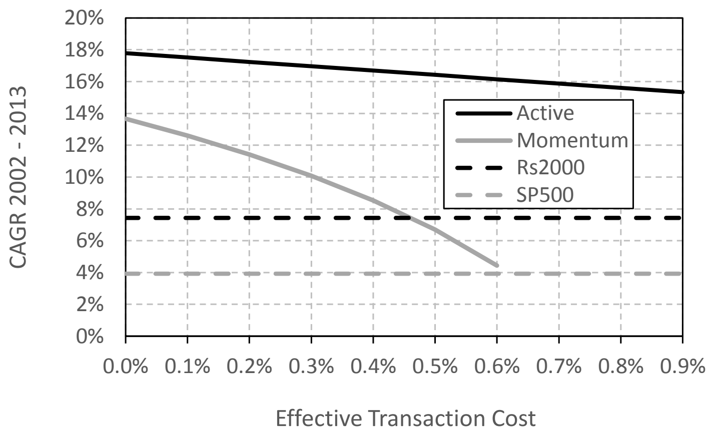


Exhibit 6: Compound annual growth rate (01.2002 – 12.2013) of the active and customer momentum portfolios and two market indexes as a function of the effective transaction cost consisting of buying and selling a particular company share as a percentage of the invested funds. The Active portfolio performs much better than the Momentum portfolio in a real-world context.

Some investment funds restrict the investable assets in a given stock to a maximum of 10% of the average daily traded volume in order to limit the implicit transaction costs [Fabozzi et al. 2010]. This rule would limit the capacity of a hypothetical fund based on the described trading methodology.

On the other hand any company pair satisfying the 10% single customer sales threshold is a potential candidate for the analysed portfolios, implying a potential of some hundreds of different shares. Standard diversification and risk management needs would also require multiplying the number of companies included. Although reaching a fund size of $100 million is a realistic target, we consider the active supply chain portfolio a niche fund, where the main purpose may be improving the diversification of larger, more traditional funds.

From the risk management perspective, the presented Active portfolio reduces the market risk due to its low correlation with the market indexes. While the methodology is not likely to recommend buying companies with diminishing earnings, we recommend regular qualitative review by a financial analyst to remove such companies from the portfolio of a hypothetical fund, which may encounter risks not being sufficiently visible in financial reports.

CONCLUSION

A new method to improve investment returns, based on the knowledge of the structure of the supply chain and the downstream financial performance is presented. This method has an operations or material flow approach in contrast to the market based work on customer momentum presented by previous authors. The investment system proposed yields annual abnormal returns of 10.1% over twelve years as compared to the Russell2000 index assuming moderate transaction costs of 0.1%.

The proposed method uses customer company quarterly reporting information. Quarterly sales of the customer company proved to be statistically the most significant driver of performance for the supplier. To optimise the parameters of the trading method, we introduced the risk-adjusted Sortino ratio instead of market prices for improved balance between risk and return. As with earlier methods, timing of transactions is critical and needs to be optimised for successful trading recommendations.

By design, the method issues annually four sets of buy/sell recommendations for the shares of a given company as compared with the monthly recommendations of the customer price momentum system. This quarterly trading frequency reduces the number of yearly opportunities for profitable transactions, but on the other hand is much less sensitive to true transaction costs including spreads - a major challenge for the earlier customer price momentum methods. Another important practical implication is the very low correlation of the proposed investing strategy with relevant benchmark indexes. Introducing the proposed trading recommendations would thus not only increase the returns of a fund, but decrease the volatility of investments. Some practical limitations of the system include the small number of supply chain partners with identifiable strong long-term links and the typically small trading volumes of supplier company shares compared to their often much bigger customers. The biggest beneficiaries of the proposed methods are thus smaller specialty funds or larger funds looking to improve their diversification and to lower the volatility.

There are several opportunities to develop the current trading method before establishing an operational supply chain fund. It is likely that integrating the methods and data sets in a multi-variable multi-period algorithm would provide better results than using just one set of data. Supply chains themselves present varying operational dynamics and investment characteristics. We suggest focusing on submarkets, industrial sectors and similar supply chain samples instead of targeting broadest possible markets. Service and financial companies were excluded from this study due to expected irrelevance in terms of ”material flows". However, this is not necessarily the case and further research on this could reveal similar behaviour in the excluded sectors as in the more physical supply chains. Finally, this study was restricted to U.S. markets. Not only could the study be expanded to other stock-exchanges but to include multinational supply chains with multiple data sources and currencies.

ENDNOTES

Parameters of the trading method

The trading method can be reformulated as

$$\text{If } [SCF_q > SCF_{q-1}] \rightarrow \text{buy on } t_{start} \text{ and sell after } \Delta t_{own} \text{ ,}$$

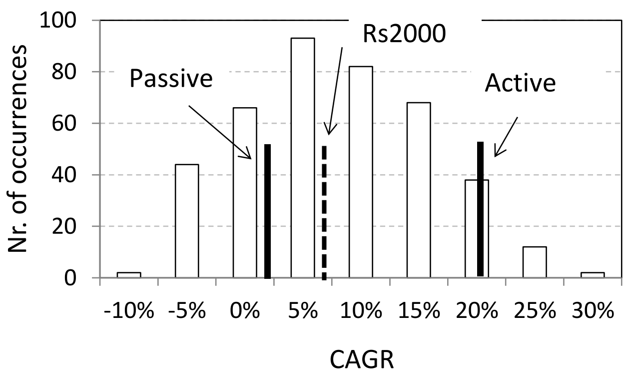
where SCF is any of the variables listed above, including e.g. Sales or Inventories. In this representation q refers to a given quarter and q-1 to the previous quarter $(1 \leq q \leq N)$, where N is the total amount of trading quarters. Financial data was available from 2002 until 2013 for most companies corresponding to N = 60 (= 12 x 4) quarters. The parameter t_{start} is the number of trading days starting from the day on which the customer company publishes its quarterly sales and Δt_{own} is the time span of the share ownership.

The optimal parameters t_{start} and Δt_{own} were determined by testing all combinations of time periods less than a quarter of a year and dividing the total available data into two subsets of the total available time period. The parameter set maximising the Sortino ratio of the earlier time period was used to compute the Sortino ratio for the later time period subset. The median values of these two parameters for these ten companies are 12 and 41 trading days respectively.

In order to avoid producing spurious results the data set was divided into two subgroups and the trading method was calibrated with one earlier subset and tested with another, later subset.

Monte-Carlo simulation of random trading

The robustness of the backtested compound annual growth rate for the high dependence supplier company pair was assessed by issuing random buy and sell recommendations for these companies. Over four hundred such randomly computed CAGR values are plotted in the histogram below. The active portfolio beats the majority of random trades. The confidence interval of the results is 92%, which is not sufficient from a theoretical point of view to exclude a statistical artefact, but is significant enough for practitioners.



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