Supply Chain Links Predictability Of Returns

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Abstract

This article shows that relationships between customer and supplier firms can be used to forecast the way suppliers returns will go. This paper also shows that different techniques are possible to exploit this phenomenon. Combining a risk parity approach and information on the customer, namely the share of sales, result in abnormal returns of 1.355%

1 Introduction

The article written by Cohen and Frazzini (2008) recently has given proof of an inattention bias in the market which contrasts the efficient market hypothesis (EMH). In their paper firms are studied by their supply chain relationship. Fluctuations of the customer firms are presented to result in an adjustment in the demand of the related supplier firm. With this known, there is a chance of predictability of the supplier firms stock prices for a period of 6 to twelve months. It is suggested that this is caused by the investors limited attention. The information available is not processed directly by the investors as they are mostly specialized in their own segments of the market. Therefor they do not react to customer changes. In accordance with this explanation the length of the lag varies with the level of investor inattention.
In Ferment et al. (2013) this research is extended by investigating the same effect but with smaller gaps between the changing portfolios. They show that the investors inattention effect appears to be bigger.

In Chaves, Hsu, Li and Shakernia (2011) the Risk parity portfolio is investigated. Investors tend to estimate subjectively on forward returns, which results in overestimating when a stock recently performed very well and underestimating when a stock recently performed badly. They show that from a Sharpe ratio perspective the risk parity construction appears to be superior to historical returns.
In this paper I will extend Cohen and Frazzini (2008) and investigate different methods to construct the supplier portfolio and different methods to rank the customer portfolios.

Additional research on the subject will give us a better view of how the market works. Irregularities in the EMH are specifically interesting for the investors as they might give insights in special ways to construct the perfect trading strategy. This will give profits to them and that might in turn lead to declining irregularities and increasing market efficiency. Furthermore it also is in interest of the investors to know about this irregularity so they know about their risks along the supply chain and can react to it.

At this stage, because this discoverd anomaly is quite recent, the conclusions are signs of speculation and therefore we need more research for this subject. In this paper I will show that by existence of the anomaly, different portfolio strategies will have a positive outcome on the profits being made. Furthermore this paper shows that the share of total sales in combination with risk parity, with abnormal returns of 1.355%, provide a better alternative for the basic investment strategy used by Cohen and Frazzini (2008).

In paragraph 2 I will discuss the articles of Cohen and Frazzini (2008) ,Chaves, Hsu, Li and Shakernia (2011) and Ferment et al. (2013). In paragraph 3 the data being used is discussed. In paragraph 4 the methods of the research will be explained. In paragraph 5 I show you the results of my research. Paragraph 6 will end with a conclusion.

2 Literature

Investor inattention is tested in Cohen and Frazzini(2008) by looking at the supplier-customer links between different firms. It is shown that the customer stock prices have a significant effect on the stock prices of their supplier firms. They show the effect is delayed. For example, a large drop in the customer firm stock leads to a gradual decrease of the suppliers stock price in the following months. The price difference of the customer stock is not directly incorporated into the suppliers stock price, which suggests that investors are inattentive to the news of linked firms. The supplier-customer links are based on reports of supplier firms in which they have to provide all their customers which are greater than 10% of their total sales.

In Cohen and Frazzini (2008) the strategy of buying supplier stocks is based on the performance of the customers. Each month all supplier firms are ranked based on their customers returns. These portfolios are divided into 5 quintiles, with in the first quintile the best 20% performing customers and in the fifth quintile the 20% worst performing customers. The long short strategy based on this information is to buy the supplier stocks in the first quintile and sell the supplier stocks in the fifth quintile. This financing portfolio is called the customer momentum portfolio. This portfolio has significant abnormal returns, which is shown by the three, four and five-factor model. In Ferment et al. (2013) they replicate Cohen and Frazzini (2008) using the same techniques as mentioned in their paper. In addition they use higher frequency data to check what happens if the portfolios follow up sooner. They show evidence for the fact that using the customer momentum portfolio, the profit being made when using the monthly strategy is less than using the weekly strategy. This means that the longer you wait to buy the stock, the more the news of the customer is incorporated into the supplier stock.
Ferment et al. (2013) also investigated the effect in more recent times. They show weak evidence of declining of the effect of inattention of the investors by using a moving window.

In Chaves, Hsu, Li and Shakernia (2011) returns between the risk parity portfolios and other asset allocation strategies are compared, such as minimum variance, equal weighting, mean-variance optimization and the 60/40 equity/bond portfolio. In the classical 60/40 equity/bond portfolio the risk is dominated by the stock market since that is very volatile. From a risk perspective the 60/40 portfolio is mainly an equity portfolio. With this in mind, the 60/40 gives little diversification despite the fact that it looks very well-adjusted. Risk parity is an approach to portfolio management which pays attention to the allocation of risk. The risk parity portfolio is able to get a higher Sharpe Ratio.

In Chaves, Hsu, Li and Shakernia (2011) it is shown that the equal weighted portfolios and the risk parity portfolios have been much more stable in their Sharpe ratios over the last 30 years. The paper also states that risk allocation is much better diversified by risk parity than to the equal weighted portfolio. Chaves, Hsu, Li and Shakernia (2011) most essential evidence is that they show that risk parity can be greatly dependent on the investment universe. It is needed to do further research to find out what asset class to include in the risk parity.

3 Data

The most important information that is needed for doing the research are the customer supplier links which are provided by Frazzini [1]. According to the U.S. law companies are obliged to publish any industry segment that accounts for more than 10% of their yearly sales. This law makes it possible to do research along the U.S. supply chains. The customer supplier links provided by Frazzini contain the yearly total sales for every supplier and the share of the sales of their customers.

For the analysis of the different customer portfolio weighting systems I use the same data as in Ferment et al. (2013) what they use for the value weighted portfolio. This means that firms for which the total sales, or the actual sale size is unknown or is not a trustworthy value, are excluded from the research. Firms are also excluded when they dont meet the 10% law as mentioned above. For the weighting schemes of the supplier portfolios, the combined shares of the customer firms are used.

The customer supplier links are derived from companies annual reports. To make sure that the relationships between customer and supplier are known by the investors, there is a six months waiting time before the information is used to form a supplier portfolio. After this waiting time the data will be used for a period of twelve months or until a new company report is made. This is reasonable as we regard annual reports.

The data of the stocks of the companies involved in the research can be found in the CRSP database. As Cohen and Frazzini (2008) I'll be using the data of the period 1980 till 2004 to make the analysis. For more recent data, 2005 till 2013, I will use the COMPUSTAT monthly database, as I am provided with the gvkeys of companies instead of permnos. These recent data unfortunately lack the total sales of the supplier companies which give me the problem to create the sale shares of the customers.

For the Risk parity approach I use the data between 1981 and 2004 in the same way as mentioned above. For the risk allocation I calculate the standard deviation of the last 12 months of each stock. I choose for 12 months so I dont lose too much data. To obtain the three-factor alphas

[1] $http://www.econ.yale.edu/\sim af227/data\_library.htm$

and excess returns I use the risk-free return rate and the Fama-French factors. These can be found on the website of Kenneth R. French [2]

Just like Ferment et al. (2013) I decided to delete all stock permutations which have a stock price below the 5 dollars. I expect that the returns out of this stock show highly volatile returns which might lead to different results. Cohen and Frazzini (2008) state that it does not make a significant difference. Therefore I exclude these values in accordance with their research. For the risk parity approach highly volatile stocks may cause serious problems.

4 Method

According to Cohen and Frazzini (2008) supplier firms have a delayed price reaction to their customer firms. Every month, I make the customer portfolios and rank them from high to low and put them into 5 quintiles. In the first quintile are put all the matched supplier firms from the 20% worst performing customer portfolios. In the fifth quintile are the matched suppliers of the 20% best performing customer portfolios. By going short in the stocks which are in the first quintile and by buying the stocks in the fifth quintile the customer momentum portfolio is created. The selling and buying will be done with different portfolio strategies as explained later.

To make the customer momentum portfolio I start with creating the customer portfolio of each supplier firm, for every month the data is available. I do this with two different methods. In the portfolio with equal weights, the weights of the customers linked to the same supplier in the same month are divided equally. In the value weighted portfolio the customers linked to the suppliers are weighted according to their share of the total sales. After that, the weights are adjusted so they add up to 1. To give an example, supplier 1 has two customers, namely customer A and customer B. Customer 1 is responsible for 30% of the total sales of supplier 1 and customer B is responsible for 10% of the total sales of supplier 1. The share of total sales is 40%. Customer A has three times as much influence as customer B which results in a weight of customer A of 3/4 and a weight of customer B of 1/4 .

4.1 Ranking Customer Portfolios

For the customer portfolio ranking I use the value-weighted method to make customer portfolios. In Cohen and Frazzini (2008) all the customer portfolios available in a certain month are weighted equally to rank them into the 5 different quintiles. To investigate whether this can be done better I give weights to the customer portfolios. These weights are equal to the share of total sales of the customer portfolio. The weights dont need to add up to one, because only the order of height is important to create quintiles and not the exact values. Since the idea is that higher total sale shares should be a better predictor for the supplier returns, I put the total customer shares into different segments. To not overweigh the highest shares I stop at a weight of 6. This means the highest weight will have 6 times as much power as the lowest weight. To give new values to the Customer portfolio return I use formula (1).

[2] $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html$

$$Customerportfoliovalue_i = weight_i * Customerportfolioreturn_i \quad (1)$$

Table 1: **Segment Weights**

Share of total sales	0.10-0.15	0.15-0.20	0.20-0.25	0.25-0.30	0.30-0.35	0.35+
Weight	1	2	3	4	5	6

4.2 Weighted supplier portfolios

I investigate in two different ways the effectiveness of risk parity. The first method is to look for risk parity on itself. The second method I combine risk parity with the total share of sales of the customer portfolio. Again under the assumption that the bigger the share of sales , the more value it gives to the predictability. For comparison I use a method in which I make weights in the supplier portfolio only on the total share of sales.
To check whether risk parity on itself has any positive effect on the outcome I use the equal weighted customer portfolios. Just like Cohen and Frazzini (2008), I put the supplier stocks into 5 quintiles according to the height of their customer portfolios. Instead of going short in quintile 1 and going long in quintile 5, I use the risk parity approach to create supplier portfolios. For every supplier at time t, I create a risk index R_i by taking the standard deviation of the last twelve returns of supplier i. To compute the weights I use formula 2. Note that the firms with a bigger risk get a lower weight. For the second method I use different weights. I muliply the factors by the total share of sales. This means more value is given to the customer portfolios which are built up by bigger or more firms. This can be found in formula 3.

$$W_{i,t} = \frac{1/R_{i,t}}{\sum_{j=1}^{n} 1/R_{j,t}} \quad (2)$$

$$W_{i,t} = \frac{S_i/R_i}{\sum_{j=1}^{n} S_j/R_j} \quad (3)$$

To test whether the customer momentum portfolio outperforms the market, I use the CAPM and the three factor model by Fama-French. When the supplier firms are divided into the five different quintiles, I calculate the average monthly return in every quintile. The risk free rates needs to be deducted so the excess returns can be calculated based on the CAPM in the formula below. Another way to look at the performing of the customer momentum portfolio is to analyze the abnormal returns. The abnormal returns can be calculated by looking at the alpha in the Fama French three factor model at the second regression below. In these equations, (4) and (5), r_i is the average monthly return over all suppliers in the concerning quintile, R_f is the Risk-free rate and K_m is the return of the total stock market. SMB stands for small minus big(market capitalization) and HML stands for high minus low (book to market ratio) factor.

Table 2: **Monthly quintile returns for the period 1981 − 2004**

Panel A: Equal Weights	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0.734***	-0.362*	-0.079	0.120	0.334	1.069***
Three-factor alpha	-0.707***	-0.459**	-0.209	-0.004	0.354*	1.061***
Panel B: Value Weight	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0.862***	-0.329	0.102	0.193	0.166	1.029***
Three-factor alpha	-0.843***	-0.408**	-0.047	0.074	0.260	1.103***

*All returns are in excess of the risk-free return rate. ***, ** and * indicate that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

$$r_i - R_f = \alpha_i + \beta_{3,i}(K_m - R_f) + \epsilon_i \tag{4}$$

$$r_i - R_f = \alpha_i + \beta_{3,i}(K_m - R_f) + b_{s,i}SMB + b_{v,i}HML + \epsilon_i \tag{5}$$

5 Results

This section will show you the results of the research in the same order as the methods are explained. To have a good comparison I show the basic outcomes of the quintiles and the long short portfolio with the same manipulated data as in the methods for the risk parity approach. In Table 2 you find these results for equal weighted customer portfolios and value weighted customer portfolios.

Table 2 shows the excess returns and the three-factor alphas of the basic two methods. These results are established with the data from 1981-2004. In these results we see that there is a positive trend through the quintiles. However, it is striking that the fourth quintile in the value weighted method is higher than the fifth quintile. Even though the values of quintile 5 dont differ significantly from zero, they do differ significantly from the lowest quintile. Therefore I can conclude that the performance of the fifth quintile is better than the performance of the first. In this period, based on the customer momentum portfolio, it would have been possible to generate excessive returns. According to the three-factor alpha the value-weighted method performs 1.103% better than the market.

5.1 Ranking Customer Portfolios

The following results are from the different methods in which the customer portfolios are ranked according to their return and total share of sales. In Table 3 the results can be found for the method with the customer portfolio value of total share of sales times the return and for the method of the segmented values.

From the results in Table 3 it can be seen that the ranking of customer portfolios improves the long short portfolio drastically. What you can see as well is that the quintiles are perfectly ascending. Compared to the basic value-weighted method, the significance has also improved by

Table 3: **Monthly quintile returns for the period 1981 − 2004**

Panel A: SOTS ratio	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0. 0.785**	-0.719***	-0.007	0.184	0.422	1.206***
Three-factor alpha	-0.768***	-0.743**	-0.052	0.127	0.432*	1.20***
Panel B: Segments	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0.918***	-0.720***	0.022	0.215	0.474	1.392***
Three-factor alpha	-0.934***	-0.765***	0.014	0.105	0.530**	1.464***

*All returns are in excess of the risk-free return rate. ***, ** and * indicate that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

the estimation of the abnormal returns. The expectation of improvement by giving value to the total share of sales and take this into account by deciding which supplier firms will go in which quintile holds for this period. The method of the segmented value assigning performs even better than the proportionally weighted method This weakens the importance of the total share of sales, since in the method of segmented value the total share of sales above 35% are all rated the same. This means that a difference from 10% of total shares to 20% of total shares is weighted heavier than the difference between 60% en 70%.
An explanation could be that when the total share of sales is very high, the customer portfolio often consists of more customers. Since the lowest quintile differs more than the highest quintile it might be that negative performing customers have a greater impact than good performers.

5.2 Weighted supplier portfolios

In Table 4 the results of the long short portfolio can be found. The research whether risk parity gives better results are shown through the three methods.

Table 4: **Monthly quintile returns for the period 1981 − 2004**

Panel A:Risk parity	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0.688***	-0.256	0.009	0.189	0.368*	1.056***
Three-factor alpha	-0.763***	-0.433**	-0.253	-0.041	0.252*	1.014***
Panel B: SOTS/Risk	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0.978***	-0.246	0.13	0.470	0.339	1.317***
Three-factor alpha	-1.08***	-0.391*	-0.18	0.339	0.275	1.355***
Panel C: SOTS	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Excess returns	-0.967***	-0.435	-0.133	0.457	0.295	1.264***
Three-factor alpha	-0.985***	-0.504**	-0.215	0.451*	0.414	1.309***

*All returns are in excess of the risk-free return rate. ***, ** and * indicate that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

In Panel A of Table 4 the results of the risk parity approach can be found. As well as in the regular long short portfolio, the values of the quintiles are perfectly ascending. Furthermore the Long/Short portfolio is highly significant. Out of the results there can be concluded that risk parity on itself does not really do a better job than the normal portfolio strategy which can be found in Table 2. In fact, risk parity has a lower performance. However, in Chaves, Hsu, Li and Shakernia (2011) they compare the different techniques by looking at the Sharpe Ratios. For the Long/short portfolio the Sharpe Ratio is higher for the risk parity approach than for the normal method. When we add the share of total sales to construct the supplier portfolio we see a great difference between the risk parity approach and the combination of share of total sales and risk parity. This can be seen in panel B. The striking point is that quintile four performs better than the last quintile. There is as well no significance in the fifth quintile but there can be stated that the first and last quintile differ significantly from each other. The Sharpe Ratio of the share of total sales and risk parity is slightly better than the risk parity alone of which we can conclude that adding the share of total sales gives a better investment performance. In panel C of Table 4 the results of making a portfolio in all the quintiles by making weights out of the share of total sales are shown. Compared to the results in panel B the performance is a little weaker. However, it does outperform the risk parity approach, but when we look again from a Sharpe Ratio perspective we find that the risk is better managed with the risk parity approach. The combination of share of total sales and risk parity outperforms the two approaches when we look at higher returns as well as Sharpe Ratio. With an abnormal return of 1.355% there can be concluded that the share of total sales and the risk parity combined have a good effect on the returns.

Method	**Sharpe Ratio**
Risk parity	0.134
Share of total Sales / Risk	0.140
Share of total Sales	0.128

6 Conclusion

Just like the paper of Cohen and Frazzini (2008), this paper shows proof of traders inattention on the financial stock market. Abnormal returns can be generated because of the fact that supplier stocks follow up their customers. My paper also shows that different techniques and strategies result in better performances, as well from a profit point of view as from a Sharpe Ratio perspective. With an abnormal return of the customer momentum portfolio of 1.355% this paper offers a new view in the extension of Cohen and Frazzini (2008).

The two different strategies discussed in this paper give different insights. At first I tried to give the customer portfolios a different structure which causes the supplier portfolios to be in different quintiles. The second strategy in this paper is to create weighted supplier portfolios. Both strategies turn out to be successful in generating abnormal returns when combined with the right technique. The first strategy is build up by two different techniques. The segmented values outperform the technique of the ratio.

However, the segmented values are values which are arbitrary. The intuition behind these segments is that a higher share of total sales must weigh heavier than a lower share of total sales. However, if the segments keep on going up the weighting value might get too large compared to the lower segments. Further research is needed to get a real understanding of the segments and explore the possibilities of improving. The segment technique performs very good, when looked at returns as well as from a Sharpe Ratio perspective, but needs to be tested for more recent data. Since the other technique is weighted proportionally this gives automatically a better intuitive reliability. The performance is, with an abnormal return of 1.20%, lower than the segment technique but gives better returns than the basic methods. The same goes for this technique, further research is needed to test whether this also gives good results in recent times. The research to make a better supplier portfolio showed positive results when looked at the Sharpe Ratio. An interesting result is that the share of total sales has a great influence on the outcome. With abnormal returns of 1.355% and a Sharpe Ratio of 0.14, it can be stated that the influence of the share of total sales in the combination of risk parity is very profitable. The investors inattention is not only present but can be exploited as well. Again, further research on recent developments can give more insights in the current situation on the market. Whether the anomaly still exists is unknown, but this paper shows that when this does exist, it can be very profitable when investors look at different portfolio strategies, in general the importance of the share of total sales of customer firms, before making the quintiles and at the moment of investing in the lowest and highest quintile. Furthermore, this paper shows that risk parity does give a better Sharpe Ratio for the period investigated. Both the excess and abnormal returns get higher when combined with the share of total sales.

Unfortunately this paper doesnt give special insights in the recent developments of the anomaly in the efficient market hypothesis. This is due to the information available at the moment of research. The total sales available in the databases didnt match the firms which are used for the customer supplier links. The claims made in this paper are based on the information available from 1981 till 2004. Another point of interest is that the research of Cohen and Frazzini (2008), as well as this research, is executed with the data of American customer and supplier firms, which means there is still space for research left to investigate the investors inattention bias in the rest of the world.

References

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