Analysis of Recent Changes in Supply Chain Link Predictability

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Abstract

In this paper I will extend the research of Cohen and Frazzini (2008) and Ferment et al. (2013) and analyze supply chain predictability in the period 2005 - 2013. Cohen and Frazzini (2008) showed prove for an anomaly contrasting the efficient market hypothesis, caused by investor inattention. Using portfolios constructed by customer performance I will demonstrate that the anamoly described by Cohen and Frazzini is still existant and makes it possible for a self-financing portfolio to realize excess returns. I will show that although the anomaly is still prevalent, the significance has diminished over time. I will make use of equal weighted as well as value weighted portfolios. Additionally, I will analyze weekly stockdata as an extension on the regularly used monthly time interval, and show that this does not improve the significance of the results. I will also demonstrate that the use of a moving window suggests the anomaly is not diminishing, and that the use of deciles instead of quintiles yields improved results.

1 Introduction

In their 2008 paper Cohen and Frazzini demonstrated that signs of investor inattention are apparent in the market. Specifically, they showed that by analyzing a supplier firms customers the supplier firms own returns show predictability. They attribute this anomaly to an information related asymmetry in the market, which contrasts the efficient market hypothesis (EMH).

In the 2013 thesis of Ferment et al. the results of Cohen and Frazzini (2008) are successfully replicated. The thesis also aimed to analyze the anomaly in a more recent time period, specifically in the years 2005 - 2013. They failed to find any significant results, and could eliminate the recent financial crisis as a possible explanation. Two other possible explanations could be made regarding the lack of significance. On the one hand it seems possible that the anomaly has faded over the years, possibly due to a growing awareness of this anomaly caused by scientific papers such as Cohen and Frazzini's (2008). On the other hand a second explanation could be found in the thesis methodology, as it used a rather crude algorithm to link customer and supplier firms.

In this thesis I continue the research of the recent development of the investor inattention anomaly. By eliminating the problematic aspects of the second explanation I will try to demonstrate that either the anomaly has actually become less significant or, conversely, that the anomaly is ever apparent in the market. To give further insight in the behaviour of this anomaly over time, I have included a moving window analysis. I will also make a minor adjustment to the manner in which the anomaly is revealed, by adjusting quantile sizes, and show that this generates significantly better results.

In section 2 I will describe the results of the existing literature. Section 3 will describe the datasets being used in the research, and the method will be explained in section 4. The results will be presented in section 5 and will be followed by a brief conclusion in section 6.

2 Literature

Cohen and Frazzini (2008) analyze firms across their supply chain. They show that the returns of supplier firms reveals a lagged reaction to fluctuations of their customers returns. The delay could be explained by investor inattention, and they suggest this is due to investor specialization. Accordingly, they demonstrate that this anomaly is weaker if more investors are focused on both the supplier and the customer firms.

Due to SFAS regulation[1] supplier firms are obliged to publish customer firms that account for more than 10% of their total sales. This has made the research possible, and opens up various weighting schemes whereby customers are weighed according to their share of sales. Using value instead of equal weights yielded slightly more significance.

Cohen and Frazzini (2008) also demonstrated that it is possible to realize abnormal returns making use of the investor inattention anomaly. They sorted supplier firms according to their customer performances and constructed a self financing portfolio which went short in the worst performing quintile and long in the best performing one. The abnormal return they realized was 1.555% on a monthly basis, replication by Ferment et al. (2013) yielded a similar return of 1.255%.

The Ferment et al. (2013) thesis also extended the Cohen and Frazzini (2008) paper by analyzing a more recent time period, using higher frequency data and constructing a moving window. The use of higher frequency data, specifically weekly instead of monthly, resulted in even higher significance and abnormal returns. Making use of a moving window suggested that the investor inattention anomaly might be diminishing, as was also suggested by the recent time period analysis.

Similar research has also been done on other terrains. Most notably, the Menzly and Ozbas (2010) paper shows a similar predictability of returns across different industries. Their research did not analyze individual firms, but industries as a whole.

3 Data

The return data as well as customer - supplier links are provided by the COMPUSTAT database. I will use data for the time period 2005 - 2013, and use gvkeys as the relevant company codes. Monthly as well as weekly data will be used, monthly as this is in accordance with the existing literature and weekly because it has been demonstrated in the 2013 thesis of Ferment et al. that this yields even more significant results. Monthly data is directly provided by the COMPUSTAT

[1] Regulation SFAS No. 131

database, for the weekly data I will retrieve the daily COMPUSTAT data and transform these to weekly time intervals.

Small stocks usually show high volatility which might interfere with results, and I therefore rid the data of all stock changes that results in a stock price lower than 5 dollars. According to Cohen and Frazzini (2008), excluding these does not make a significant difference and I choose to follow their paper by maintaining the exclusion.

With regards to the equally weighted portfolio I use all viable customer-supplier links, which means I also include those for which I do not have any sales size, or those companies whose sales size is suspiciously low. For the value weighted portfolio method I eliminate those companies which do not have sales info, as these can impossible be given a valuable weight, and those whose sales account for less than 10% of total sales, as this was the limit of the SFAS regulation and I suspect that companies who do not make this limit do not have an incentive to disclose this information. I will regard these data as compromised.

To make use of the moving window analysis I use the data generated by the Ferment et al. (2013) paper containing the quintile returns for the period 1996 – 2004 as I will use a moving window of 10 years, and this window size will necessitate the data of this previous time period.

As the to be investigated time period contains the global financial crisis, some descriptive statistics of this period might be valuable. Table 1 was provided in the Ferment et al. (2013) thesis and shows that the pre-crisis years (2005 – 2007) show a significantly lower volatility than that of the entire period, while their means are similar. The data used for these statistics is the monthly stock database of COMPUSTAT.

Table 1: **Descriptive statistics of the stock data**

Period	2005-2013	2005-2007
Mean	0.9018	0.9078
Standard deviation	24.8027	13.575

This table shows the mean and standard deviation of the monthly COMPUSTAT stock data.

The customer - supplier links only contain the actual names of the customer firms. I will manually match these names with the corresponding gvkey codes of these companies, as these codes are needed to investigate these firms returns.

I obtain the necessary data to calculate the excess returns and the three-factor alphas, for both monthly and weekly intervals, on the website of Kenneth R. French.[2]

[2] *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

4 Method

The first and most pressing issue is the linking of the customer and supplier firms. As stated above, this will be done manually. The reason behind this is that the names are written differently in the gvkey code list and the customer - supplier links list, which makes it impossible to use a string comparison algorithm to accurately match the name with the gvkey code (for example, one list might use abbreviations while the other does not). The manual linking is labor intensive but perhaps the most crucial part of the research, this data is to be the foundation of what is to come. The Ferment et al. (2013) paper did use the flawed string comparison algorithm and out of the 44,563 unique firms it found 26,279 succesful comparisons. The stricter manual linking resulted in 3,852 comparisons which equates to 40,067 actual customer-supplier links.

After the data is sufficiently adjusted, I will follow the methodology of Cohen and Frazzini (2008). For every month, I sort the suppliers based on the performance of their customer firms. To do this, I generate a portfolio of all relevant customer firms and weigh their returns either equally or based on their share of that months sales (which is referred to as value weighted). I then divide the suppliers firms up in quintiles, such that the first quintile contains the suppliers with the worst 20% performing customers and the fifth quintile the suppliers with the best 20% customer performance. I construct a self–financing portfolio by going short in the first quintile and going long in the fifth. This portfolio is called the customer momentum portfolio and its performance will be a cornerstone of the results as it might provide us with significant excess returns.

The value weighted portfolio will take the sum of the sales of all the linked customers to be the total sales at this time. In other words, the weights in the value weighed portfolio for a supplier on a specific time will always add up to one.

To determine if the customer momentum portfolio performs better than the market, I make use of the CAPM and the Fama-French three factor model, as is done by Cohen and Frazzini (2008) and Ferment et al. (2013). I calculate the average return for the different quintiles, and substract the risk-free return in order to calculate the excess return based on the CAPM model as shown in equation (1) or the abnormal results based on the Fama-French three factor model as shown in equation (2).

$$r_i - R_f = \alpha_i + \beta_{3,i}(K_m - R_f) + \epsilon_i \tag{1}$$

$$r_i - R_f = \alpha_i + \beta_{3,i}(K_m - R_f) + b_{s,i}SMB + b_{v,i}HML + \epsilon_i \tag{2}$$

r_i is the average monthly return over all suppliers in the concerning quintile. R_f is the Risk-free return rate and K_m is the return of the total stock market. SMB is short for Small Minus Big and should be interpreted as market capitalization, while HML is an abbreviation for High Minus Low and should be interpreted as the book-to-market ratio.

The use of higher frequency data might yield more significant results which is especially viable as the 2013 thesis could not find any significance in the period to be investigated. I retrieve the daily stock returns and transform these to weekly returns. I will use fridays as the day that determines the stockprice of this week and the previous week, and those prices both determine the return of that week. If no stockdata of friday is available, thursdays or even wednesdays will be used instead.

After this, the method will be similar to the one explained above. I will do this using the equal weighted data scheme, as the difference between the two is small and the equal weighted portfolio is a more efficient method which is especially viable as the use of weekly data means our total dataset is a lot larger.

To investigate the behaviour of the anomaly over time I will make use of a moving window. I employ a 10 year window, as is done in the Ferment et al. (2013) thesis, and calculate the abnormal returns on a one year step basis. I will determine the intercept and trend for the first and fifth quintile, as well as for the customer momentum portfolio.

I further expand on the research of the existing literature by adjusting the quantile size. In addition to the division of the portfolio into quintiles each containing 20% of the supplier firms, I will experiment with deciles each containing 10% of the supplier firms. Intuitively, the anomaly should be strongest in the extremes. On the other hand, robustness of quantile performance would be improved by large quantiles. These contrasting forces have lead me to the conclusion that 10 quantiles could yield improved results without losing robustness and significance, the use of even more quantiles would not be feasible given that our dataset averages 261 supplier firms on a monthly basis.

5 Results

5.1 Monthly Data

Table 2 shows the excess returns and the alphas of the three-factor Fama French model for the time period of 2005 – 2013 using monthly data. The first thing we notice is that the results do resemble those found by Cohen and Frazzini (2008) for the period of 1980 – 2004. This is in contrast with the results found by Ferment et al. (2013) which was to be expected, as their string comparison algorithm was not thrustworthy.

Specifically, we notice that for both weighting schemes the lower quintiles show very high significance. However, the long–short portfolio does not show this same trend. We only find a significant return for this customer momentum portfolio with the equal weighting using the CAPM model. It might be notable, though, that this portfolio analyzed with the three-factor Fama French model barely fails to be significant with a significance of 10.9%.

It is interesting to see that the value weighted scheme is outperformed by the equally weighted method. This is in contract with the literature, and in a way counterintuitive. We do find higher significance for the fourth quintile, but no significance at all for the customer momentum portfolio.

The financial crisis could still be a factor of importance, making it hard to find significant excess returns for the customer momentum portfolio. Table 3 shows the results for the equally weighted method split up into the time periods 2005 – 2007 and 2008 – 2012. Interestingly, the pre-crisis period of 2005 - 2007 actually seems to be most problematic, whereas the crisis years outperform previous results by finding significant excessive returns for the customer momentum portfolio using both the CAPM and three-factor Fama French model.

Table 2: *All returns are in excess of the risk free rate. Under every result are the t-values to test if the alphas differ significantly from zero.***, ** and * indicates that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

Panel A: Equal weights	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Three-factor alpha	-0.981***	-0.878***	-1.377***	-0.243	-0.456*	0.523
Excess returns	-0.936***	-0.848***	-1.334***	-0.217	-0.400	0.536*
Panel B: Value weights	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Three-factor alpha	-0.870***	-0.947***	-0.950***	-0.497**	-0.421	0.449
Excess returns	-0.908***	-0.974***	-0.973***	-0.532**	-0.470*	0.439

Table 3: *All returns are in excess of the risk free rate. Under every result are the t-values to test if the alphas differ significantly from zero.***, ** and * indicates that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

Panel A: 2005 – 2007	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Three-factor alpha	-1.041***	-1.423***	-2.657***	-0.828	-1.086***	-0.045
Excess returns	-1.231***	-1.582***	-2.666***	-0.765	-1.240***	-0.009
Panel B: 2008 – 2012	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Three-factor alpha	-0.933***	-0.499*	-0.726***	-0.028	-0.141*	0.792*
Excess returns	-0.736**	-0.418	-0.582*	0.104	0.092	0.828*

5.2 Higher Frequency Data

Table 4 shows the results for the weekly stock data regressions. It is clear that there is high significance for the first, third, fourth and fifth quintile, while the second and the customer-momentum portfolio remain insignificant. This is unexpected, as Ferment et al. (2013) suggested that the use of weekly data would improve significance. It is not, however, unintuitive, as stockprices show a smaller fluctuation on a weekly basis compared to a monthly basis, and such fluctuations are less informational dense.

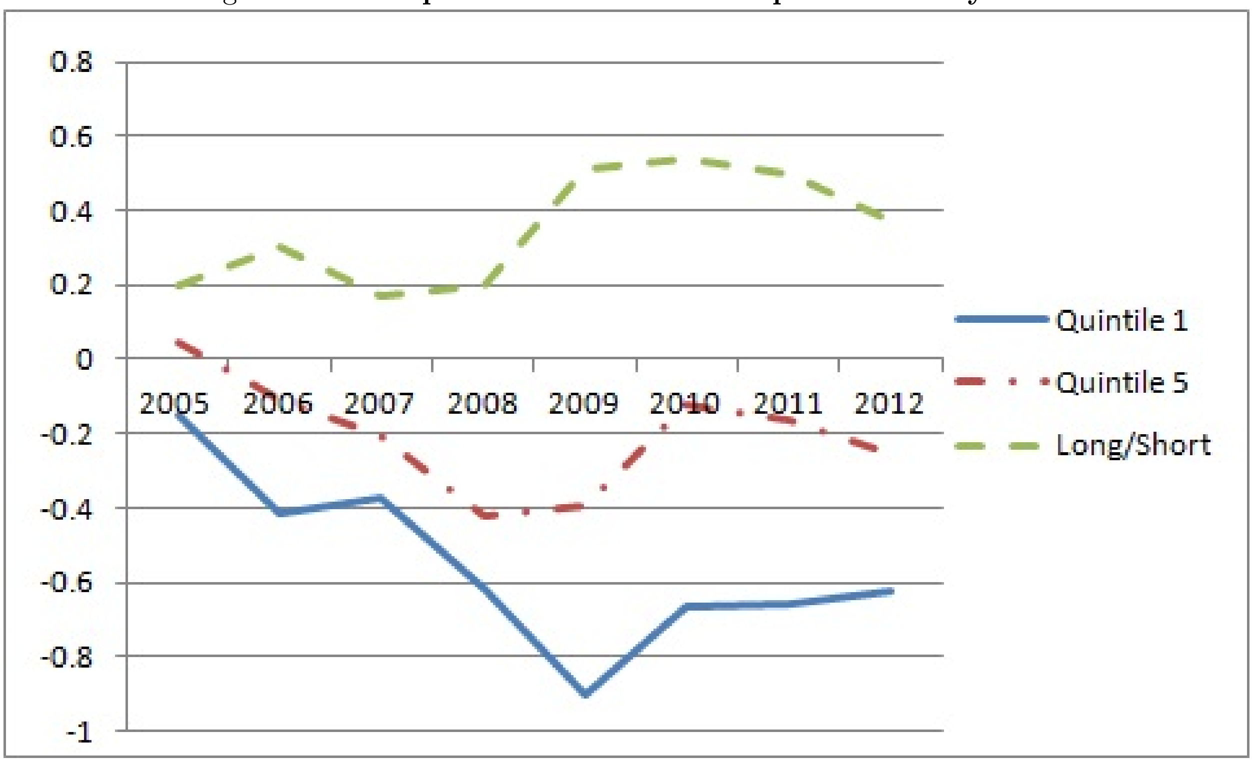
Table 4: *All returns are in excess of the risk free rate. Under every result are the t-values to test if the alphas differ significantly from zero.***, ** and * indicates that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

Panel A:Weekly Data	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**L/S**
Three-factor alpha	-0.030***	0.082	-0.032***	-0.0.028***	-0.028***	0.002
Excess returns	-0.031***	0.083	-0.032***	-0.028***	-0.028***	0.003

5.3 Moving Window

Figure 1 shows the development of the three-factor alpha over time. The year indicates the last year of the current window, so the datapoint for 2005 is calculated with a window consisting of the period 1996–2005. As was obvious given the results presented above, both the first and fifth quintile are almost exclusively negative. The customer momentum portfolio does not show a diminishing trend, and although it shows fluctuations it has a rather constant impression. The intercept and trend of the simple lineair regression on the first and fifth quintile, as well as the customer momentum portfolio, can be found in Table 5. It is interesting to note that instead of diminishing, the customer momentum portfolio actually seems to increase. The figure further suggests that this might be caused by the economic crisis, which started in 2008. This is in line with the above results which showed a much stronger effect in the crisis years (2008 – 2012) than the pre-crisis years (2005 – 2007).

Figure 1: **Development of three-factor alpha over the years**



This graph plots the three-factor alpha over the years using a moving window of 10 years with 1 year steps.

5.4 Deciles

Table 6 shows the results of the equally weighted method using deciles instead of quintiles. Overall, we notice that the significance of the quantiles is comparable, but we now notice that the customer momentum portfolio yields significant results for both methods. This is an improvement over the results obtained using the quintiles, as only the three-factor alpha method yielded a significant cus-

Table 5: *This table show the results of the regression on the alphas of the different quintiles using a moving window. ***, ** and * indicate that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

	intercept	years
Quintile 1	-0.313**	-0.068**
Quintile 5	-0.113**	-0.025**
Long/Short	0.199**	0.043**

tomer moment portfolio performance. These results not only support the notion that the anomaly is still apparent and could be used to construct self financing portfolios yielding excessive returns, but also that the use of smaller quantiles can significantly improve this.

Table 6: *All returns are in excess of the risk free rate. Under every result are the t-values to test if the alphas differ significantly from zero.***, ** and * indicates that the coefficient estimate is different from zero at a 1%, 5% and 10% confidence level, respectively.*

Equal Weights, 10% Quantiles	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	
Three-factor alpha	-1.208***	-0.859***	-1.099***	-0.641**	-1.248***	
Excess returns	-1.158***	-0.821**	-1.056***	-0.620**	-1.219***	
Equal Weights, 10% Quantiles	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**L/S**
Three-factor alpha	-0.983***	-0.613**	-0.064*	-0.379	-0.544**	0.664*
Excess returns	-0.949***	-0.588*	-0.031	-0.322	-0.492	0.666*

6 Conclusion

This more in-depth analysis of the time period 2005 – 2013 has yielded some interesting results. First of all, the preliminary conclusion of Ferment et al. (2013), that the limited attention anomaly has disappeared, can be denounced. Especially the lower quintiles show very high significance, indicating that excess (negative) returns can still be realized.

On the other hand, the self–financing portfolio did not show significant profitability. Only for the equally weighted method some significance could be found. The significance could be improved by scaling down the quantile sizes, which demonstrates that the anomaly is more profound in the extremes.

Overall, the results seem to be less significant than those of the 1980 – 2004 time period, but research around the crisis years demonstrates that the crisis is not a cause for this. Quite the contrary, the anomaly is found to be much more prevalent during the crisis years of 2008 – 2012 than in the years prior, 2005 – 2007. The reason for a generally lower significance may could be found in an increase of investor attention to the anomaly, although future research is needed to support this claim. It must be stated that the anomaly does not show a diminishing trend, and might actually be increasing. This phenomenon might, however, be attributed to the crisis, as the moving window analysis demonstrates an upward jump in 2008. Further research regarding the long-time development of the anomaly, whether the investor attention is actually increasing and in what way the crisis positively reinforces the anomaly could shed some new light on the subject.

Lastly, it is notable that the use of higher frequency data did not provide any improvements on the abovementioned results. Ferment et al. (2013) demonstrated that the use of weekly returns could lead to a higher level of significance than the monthly method of Cohen and Frazzini (2008). The results of this thesis serve to diminish such claims, as the usefulness does not seem to be a universal aspect. A possible explanation might be that the weekly effects are only apparent when the investor inattention is larger, as seemed to be the case in the 1980 – 2004 time period. The loss of significance for higher frequency data is not entirely unexpected, as higher frequency returns are generally considered to contain less information and more noise.

References

[1] Cohen, L. and Frazzini, A. (2008). *Economic Links and Predictable Returns.* Journal of Finance, 63(4): 1977-2011.

[2] Ferment, F. , Lock, J. , Moers, F. and Timmermans, R. (2013) *Supply Chain Links and Cross-Industry Predictability of Returns.* Not Published.

[3] Menzly, L. and Ozbas, O. (2010). *Market Segmentation and Cross-Predictability of Returns.* Journal of Finance, 65(4): 1555-1580.