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Abstract

We create portfolios of lightly shorted and heavily shorted stocks to test for monthly abnormal returns by using the Fama and French Three Factor Model with Momentum as well as the Fama and French Five Factor Model. We test this long-short strategy as a means of testing for market efficiency. We find that heavily shorted portfolios have lower abnormal returns in comparison to lightly shorted portfolios. Furthermore, we demonstrate that a trading strategy that goes long on lightly shorted stocks and short on heavily shorted stocks generates abnormal returns that are lower in comparison to a strategy that encompasses going long on lightly shorted stocks only. It is worth noting that it is difficult to compare long only portfolios with long-short portfolios due to the short component borrowing costs which often change on a day-to-day basis. However, even accounting for marginal borrowing costs, our results show that the long-short portfolios vastly underperform long only portfolios.

Key words: Short selling, short interest, portfolio strategy, arbitrage.

JEL classification: G12, G14,

1. Introduction

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This paper builds on the findings of Boehmer et al. (2010) which demonstrate how investors can achieve a risk-free adjusted return simply by implementing an equity investing strategy of holding a long-short portfolio based on the highest and lowest short interest ratios (SIR) and, based on new short interest data, rebalancing every month. Despite the simplicity of the strategy, we see that there are drawbacks in terms of rebalancing costs – namely that an investor would be required every month to sell and buy stocks to maintain a long-short portfolio based on new short interest data. If the investor is dealing with many buy and sell orders, this can lead to a substantial increase in transaction fees.

The goal of our research is to cover three main areas of focus. Firstly, it is to find out whether the results of Boehmer et al. (2010) remain robust after the strategy became known to the market over a period which falls after the publication of Boehmer et al. (2010). Secondly, the Three-Factor Model with Momentum (hereafter FF3M) is compared to the Fama-French Five Factor Model (hereafter FF5) to check the robustness of our results. Thirdly, to add further analysis to the study conducted by Boehmer et al (2010), we replicate the analysis for both models by using a dynamic dimension with a rolling window as well as a recursive approach to test whether our results change over time.

We form six portfolios to replicate Boehmer et al. (2010)'s strategy. We start by forming two portfolios on the 5th and 10th percentile on the SIR[3] of the previous month[4] and then two portfolios on the 95th and 90th percentile, likewise on the short-interest ratio of the previous month. Using these four portfolios, we also construct two long-short portfolios to test for significant differences between the 95th and 5th percentile portfolios and the 90th and 10th percentile portfolios. We then regress the monthly portfolio excess returns on the FF3M and FF5 factor models and report the results accordingly.

Our findings in relation to the FF3M show positive and significant abnormal returns for lightly shorted portfolios as well as long-short portfolios. We find that abnormal returns of lightly shorted portfolios with a short interest of 5% were positive with 150 basis points per month. Furthermore, abnormal returns for long-short portfolios were found to be positive with values ranging from 80 to 120 basis points per month. The results from the FF5 are quite similar to the ones related to the FF3M. More generally, the FF3M and FF5 findings show that the positive abnormal returns increase as the level of short interest declines. Secondly, and most

[3] Short-interest ratio is a metric of short selling activity and can be defined as shares sold short divided by shares outstanding.

[4] A 5th percentile portfolio means that this portfolio has the lowest 5% of short interest (number of shares sold short as a percentage of the shares outstanding) in our sample on the previous month.

importantly, our results show that even if low short interest portfolios outperform high short interest portfolios, the strategy proposed by Boehmer et al. (2010) is no longer valid owing to the positive performance of the SIR 95% portfolio.[5] If the SIR 95% portfolio had led to a negative return, then taking a short position would be a viable strategy.[6] However, this has not been the case.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the data used in this study. Section 4 presents the methodology. Section 5 presents our empirical results and Section 6 concludes.

2. Relevant literature

One of the strands of the empirical literature on short selling activity focuses on the relationship between SIR and stock returns. The findings of the academic literature are not clear cut and result in two main alternative perspectives on this relationship.

The first perspective on the relationship between short interest and stock returns is that high levels of short interest are neutral signals in the sense that they have irrelevant effects on stock returns. An empirical study testing this perspective is presented in Brent et al. (1990). By using short interest data related to a sample of 200 equity stocks listed on the New York Stock Exchange (NYSE) during the period 1981-1984, Brent et al. (1990) reported that short selling activity can be explained by arbitrage and opportunity. The former mainly includes options and convertible securities whereas the latter includes, for instance, tax-recognition as well as trade imbalances between supply and demand of securities. Therefore, in accordance with Brent et al. (1990), short selling activities do not reflect negative information. Also, Wooldridge and Dickinson (1994) found, by focusing on equity stocks listed on the NYSE, American Exchange (Amex), and Nasdaq markets over the period 1986-1991, that high levels of short selling activity are not necessarily a bullish nor bearish indicator.

The second perspective is that high short interest is a bearish signal, implying a negative relationship between short interest and stock returns. By focusing on equity stocks listed on NYSE, Amex and Nasdaq stock exchanges, several empirical studies (see, for instance, Figlewsky, 1981; Senchack and Starks, 1993; Asquith and Muelbroek, 1995; Desai et al., 2002; Christophe et al., 2004) reported evidence of high levels of short interest predicting negative returns for equity stocks. Unlike these studies, which investigated short interest and subsequent

[5] SIR is a metric of short selling activity that can be defined as shares sold short divided by shares outstanding.

[6] Boehmer et al. (2010) find that the SIR 95% portfolio with equal weighting had an average monthly return of -0.1%, which would indeed have been a negative return and a viable shorting strategy.

stock returns, Aitken et al. (1998) and Ackert and Athanassakos (2005) focused on the contemporaneous relationship between the short selling metrics and stock returns in relation to Australian and Canadian stock exchanges. As reported in Aitken et al. (1998), investigating the contemporaneous relationship instead of the predictive one was possible because, in the case of the Australian Stock Exchange, short interest data is available at a higher frequency in comparison to the US equity markets. In the Australian equity market, short selling information related to individual stocks is made available to the public immediately after execution (Aitken et al., 1998). On the other hand, as pointed out in Ackert and Athanassakos (2005), information related to short interest positions in the Canadian and US stock markets is aggregated and reported on a semi-monthly or monthly basis respectively. The findings reported by Aitken et al. (1998) and Ackert and Athanassakos (2005) confirm that in both Australian and Canadian equity markets the larger the short interest is, the more negative contemporaneous abnormal returns are.

More recent studies try to investigate whether the intensity of trading a stock and the amount of short interest might lead to different results with respect to the relationship between SIR and stock returns. For instance, Boehmer et al. (2008), using short interest data and returns of NYSE-listed stocks over the period from January 2000 to April 2004, reported that portfolios made up of heavily shorted stocks on average underperform portfolios based on lightly shorted stocks by a risk adjusted return of 1.16% (Boehmer et al., 2008). In a similar study, Diether et al. (2009) found that portfolios that are long on lightly shorted stocks and short on heavily shorted stocks can generate positive abnormal returns. However, as pointed out by Diether et al. (2009), there would be a considerable amount of trading required to capture those returns as portfolio rebalancing would be required each month to account for new short interest information. In the same vein, Au et al. (2009), focusing on the UK FTSE 350 securities, demonstrated that stocks characterised by low levels of short interest are the ones that very often experience positive abnormal returns: this is due to the hypothesis that short sellers tend to avoid stocks that have high unsystematic risk. Their findings show that a negative relationship exists between short interest and returns on stocks with high firm-specific risk, and that short selling activity is more concentrated in stocks with low unsystematic risk where the cost of arbitrage is lower. In a more recent study, Boehmer et al. (2010) found, using NYSE, Amex and Nasdaq data, that stocks with relatively high short interest experience negative abnormal returns. They also found that heavily traded stocks with low short interest experience positive abnormal returns. These positive returns in lightly shorted stocks are often larger, in absolute terms, than the negative returns in highly shorted stocks. Thus, taking a long position in a lightly shorted portfolio and taking a short position in a heavily shorted portfolio, and then rebalancing the portfolio each month, can produce excess returns beyond that of a fair asset pricing model[7]. More recently, Mohamad et al. (2013) explored the relationship between short selling and stock returns for all UK FTSE 350 stocks using a dataset for the period September 2003 to April 2010. Their findings show significantly negative abnormal returns for heavily shorted stocks. Secondly, the market seems to adjust quickly to the arrival of the short interest information. Their results also hold during periods of financial turmoil such as the 2007-2009 global financial crisis.

The empirical literature clearly indicates that short interest is used as an essential metric to understand stock returns. Our study contributes to the existing empirical literature in two ways. Firstly, since the publication of Boehmer et al. (2010), institutional investors may have adopted this strategy as a means of excess return. Studies like ours are therefore interested in whether these strategies are still valid or whether they have been arbitraged out – a key indication of market efficiency. Therefore, by using a sample of common stocks listed on the NYSE and Nasdaq markets, we test the strategy proposed by Boehmer et al. (2010) to verify whether investors can still achieve a risk-free adjusted return by holding a long-short portfolio based on the highest and lowest SIRs and rebalancing every month. We perform the empirical analysis by aggregating stocks into portfolios and grouping either lightly or heavily shorted stocks: this will enable us to verify the hypothesis that positive abnormal returns on stocks that have little short interest are larger (in absolute value) than the negative returns on portfolios of heavily shorted stocks. Secondly, our study is one of the few to analyse the relationship between short sales and stock returns using a dynamic approach. In other words, we investigate whether the results of a static regression analysis based on both the FF3M and FF5 models are still consistent in a dynamic fashion with either a rolling window or recursive regression analysis approach. This dynamic approach allows us to see changes, if any, over time for certain metrics of significance of the FF3M and FF5 models such as *alpha* and *beta*.

3. Data and variables

[7] Boehmer et al. (2010) used the Fama French Three Factor Model with Momentum as their fair asset pricing model.

To capture as much of the US equity market as possible, the data we used in this study encompasses stocks and stock returns of companies listed in the NYSE and Nasdaq over the period February 2010 to July 2017. The start date was chosen as this is when the strategy proposed by Bohemer et al. (2010) was made public. On the other hand, the choice to end our period of analysis in July 2017 was motivated by the fact that, in 2017, rates of interest were not only below historical norms but also very close to 0%, creating the low interest rate environment that characterised the US economy following the 2008 global financial crisis.

To perform our empirical analysis we used constituent stocks of the Thomson Reuters US Total Return Index including stocks listed on the NYSE and Nasdaq. As of July 2017, that index included 1,044 listed in the Nasdaq and 1,359 in the NYSE for an overall total of 2,404 equity stocks.[8] In terms of stocks reported, our dataset is smaller than the one used by Boehmer et al. (2010) which was built with data from the Center for Research in Security Prices (CRSP) database.

Our study uses monthly prices data in US dollars. Descriptive statistics of our dataset are presented in Table 1. Column (1) shows that the monthly returns were the highest (3.23%) in 2013 and the lowest (-0.02%) in 2015. The standard deviation of returns in column (2) shows that 2010 was the most volatile year with the largest returns' standard deviation (6.72%) while 2017 had some of the least standard deviation corresponding to 1.47%. Column (3) shows that the maximum average monthly return was the highest in 2010 (11.51%). On the other hand, the minimum monthly return was the lowest in 2011 (-10.43%).

Table 1: Descriptive statistics

Year	(1) Average Monthly Returns	(2) Average St. Dev.	(3) Max Monthly Returns	(4) Min Monthly Returns
2010	2.80%	6.72%	11.51%	-7.54%
2011	0.09%	6.62%	15.33%	-10.43%
2012	1.89%	3.75%	8.16%	-6.62%
2013	3.23%	3.08%	7.13%	-2.45%
2014	1.28%	3.65%	5.35%	-4.65%
2015	-0.02%	3.99%	5.95%	-5.25%
2016	2.04%	5.10%	6.76%	-8.61%
2017	1.11%	1.47%	9.29%	-1.60%

[8] The full list of equity stocks is available from the corresponding author upon request.

In this study, we are particularly interested in the short interest that our dataset encompasses. Short interest data have been gathered from the *Eikon Refinitiv* database. To perform our empirical analysis, we calculated the monthly SIR for each stock in two steps. Firstly, we divided the total number of shares sold short over the total number of outstanding shares for each stock of our dataset. Secondly, we calculated the average SIR of all stocks that are traded in that month. Table 2 presents the average distribution of SIR. Column (1) shows that 2016 is the year in which, on average, the total number of shares sold short over the total number of outstanding shares is the highest (5.78%), whereas 2013 is the year with the lowest amount of SIR on average across the dataset (4.66%). The 90th percentile in column (2) demonstrates the SIR at which 90% of all stocks on a monthly basis are below: the value was the lowest in 2011 (10.79%), whereas 2017 was the year with the highest value (14.04%). On the other hand, by looking at the 50th and 10th percentiles in columns (4) and (5), the lowest values were both in 2013: 2.78% and 0.93% respectively. Conversely, the highest values were found in 2010 (3.91%) for the 50th percentile and in 2016 (1.26%) for the 10th percentile. Table 3 shows the standard deviation of SIR for the whole sample as well as for the percentiles. If we focus on the whole sample, column (1) shows that 2015 was the year with the highest SIR standard deviation (0.37%) whereas 2013 was the year with the lowest (0.06%). Breaking down the sample by percentiles, we found that the largest standard deviations were in 2017 for the 90th percentile (0.83%), in 2011 for the 50th percentile (0.37%) and in 2015 for the 10th percentile (0.17%). Conversely, the lowest standard deviation was in 2013 for the 90th percentile (0.27%), 2013 for the 50th percentile (0.09%) and 2017 for the 10th percentile (0.04%).

Table 2: Average SIR whole sample and by percentile

	(1)	(2)	(3)	(4)
Year	Average monthly SIR	90th Percentile Average monthly SIR	50th Percentile Average monthly SIR	10th Percentile Average monthly SIR
2010	5.39%	11.42%	3.91%	1.14%
2011	5.0%	10.79%	3.60%	1.01%
2012	5.01%	10.82%	3.36%	0.99%
2013	4.66%	10.89%	2.78%	0.93%
2014	4.92%	11.70%	2.94%	0.96%
2015	5.31%	12.22%	3.29%	1.08%
2016	5.78%	13.04%	3.77%	1.26%
2017	5.75%	14.04%	3.50%	1.00%

Notes. Authors' own calculation using SIR.

Table 3: Standard Deviation SIR whole sample and by percentile

	(1)	(3)	(4)	(5)
Year	St Dev SIR whole sample	90th Percentile St Dev SIR	50th Percentile St Dev SIR	10th Percentile St Dev SIR
2010	0.16%	0.33%	0.20%	0.05%
2011	0.27%	0.42%	0.37%	0.14%
2012	0.21%	0.28%	0.23%	0.07%
2013	0.06%	0.27%	0.09%	0.05%
2014	0.26%	0.35%	0.29%	0.10%
2015	0.37%	0.71%	0.34%	0.17%
2016	0.16%	0.29%	0.18%	0.10%
2017	0.24%	0.83%	0.07%	0.04%

Notes. Authors' own calculation SIR.

4. Methodology

Our analysis explored the period after the publication of Boehmer et al. (2010) to find out whether the strategy proposed by Boehmer et al. (2010) produces similar results when applied to a similar dataset of US common stocks. There are many cases where market arbitrage takes place, making a once risk-free strategy invalid. A perfectly efficient market would remove such strategies once information regarding these strategies became public. This would account for the semi-strong form of market efficiency. It is worth highlighting that there are several drawbacks to this strategy in terms of rebalancing costs. An investor engaged in this strategy would be required to sell and buy stocks every month to maintain a long-short portfolio based on new short interest data. Thus, for an investor dealing with many buy and sell orders, this could lead to a dramatic increase in transaction fees and taxes. To test this strategy, we formed two highly shorted and two lightly shorted portfolios. The highly shorted portfolios included stocks from the 95th and 90th percentiles of the SIR distribution of the previous month. The lightly shorted portfolios included stocks from the 5th and 10th SIR percentiles. We also formed long-short portfolios to test for significant differences between the 95th and 5th percentile portfolios and the 90th and 10th percentile portfolios. The portfolios change each month depending on the SIR of the previous month and therefore the number of stocks per month in each portfolio will differ. As in Boehmer et al (2010), we used the FF3M (see Equation 1) for each of the first four portfolios and for the two long-short portfolios. We also implemented the equal weighting strategy where the composition of stocks in each portfolio are of equal weight rather than weighted by market capitalisation or any other metric. Most investors outside of Exchange Traded Funds (ETFs) tend to hold portfolios that are equally weighted when selecting equities and this construction functions to mimic their behaviour. The average investor may not be aware of the market capitalisation of the companies they hold and would have been constantly adjusting weightings based on changes in market capitalisation. The excess return of these portfolios is used as a dependent variable in a FF3M model time-series regression which is the same employed by Boehmer et al. (2010) and is specified as follows:

$$R_{it} - R_{ft} = a_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + w_i WML_t + e_{it} \qquad (1)$$

where R_{it} is return of securities or portfolio *i* for period *t*, R_f is the risk-free rate of interest (taken as the 3-month US treasury rate) for period *t* and $R_{mt} - R_{ft}$ is the market risk (MKT) premium that is the excess return above the risk-free rate. *Small minus Big* ($\mathrm{SMB_t}$) is the size factor, that is the difference between the outperformance of small firms compared to large firms for period *t*. *Book to Market* ($\mathrm{HML_t}$) factor is the difference between the outperformance of growth stocks compared to value stocks for period *t*. *Winner Minus Loser* ($\mathrm{WML_t}$) is the momentum factor, that is the difference between the outperformance of stocks, showing short term momentum over stocks without short term momentum. The last term of Equation (1), ε_i, is the error term for period *t* to account for inconsistencies in the model. The FF3M shows us where in particular the returns are coming from based on the four factors: that is, $E(R_m) - R_f$, SMB, HML and WML. The *alpha*, that is α_i, of Equation (1) will show us either the underperformance or overperformance of the model in relation to short interest: in particular, a large value of the coefficient α_i is an indication that the model is overperforming based on either high or low short interest portfolios, while a low α_i will show us that the model is underperforming based on either high or low short interest portfolios. Based on previous empirical literature (see, for instance, Boehmer et al., 2010), we expect the underperformance of heavily shorted stock portfolios (shown with a lower α_i) in comparison to lightly shorted portfolios). For comparison purposes we also use the FF5 asset pricing model of French and Fama (2015), presented in Equation (2), where profitability (RMW) and investment (CMA) factors are added to the Fama and French (1993) three factor model. The FF5 is specified as follows:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \tag{2}$$

where *Robust Minus Weak* ($\mathrm{RMW_t}$) is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, whereas *Conservative Minus Aggressive* ($\mathrm{CMA_t}$) is the difference between the returns on diversified portfolios of the stocks of low and high investment firms (Fama and French, 2015).

5. Individual portfolios

We applied both the FF3M and FF5 models to alternative individual portfolios whose descriptive statistics are shown in Table 4. Column (1) of Table 4 shows that the average monthly returns during our period of analysis were higher in the lightly shorted portfolios (SIR 10% and SIR 5%) than the heavily shorted portfolios (SIR 90% and SIR 95%), therefore demonstrating the better performance of the lightly shorted stocks over the heavily shorted stocks. As illustrated in column (2), heavily shorted portfolios show much larger standard deviations (0.06% for the SIR 95% as well as for the SIR 90%) as opposed to lightly shorted portfolios (0.04% for the SIR 5% and 0.03% for the SIR 10%). The much larger standard deviation in heavily shorted portfolios compared with their lightly shorted counterparts could be a result of short squeezes amplifying the upside and speculators shorting on the downside. This is because the stocks with high short interest are more likely to interest speculators over investors since volatility is beneficial to the speculator as it creates low prices to buy and high prices to sell. The key difference between a speculator and an investor is that a speculator is often only interested in price movements while an investor is interested in the underlying business the stock represents as a whole. The results for the kurtosis presented in column (4) do not show any definite trend in this case as to whether heavily or lightly shorted portfolios have fat tails. Column (5) indicates a negative skewness in all portfolios but the short-long ones (that is SIR 5% - SIR 95% and SIR 10% - SIR 90%), favouring more months of portfolios holding higher returns than lower returns. This would make sense since the purpose for holding stocks is to gain a return rather than to make a loss. Column (6) shows that heavily shorted portfolios such as the SIR 90% and SIR 95% were the ones with the highest maximum returns. On the other hand, column (7) highlights that the short-long portfolios have the lowest minimum returns.

Table 4: Descriptive Statistics for Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Portfolio	Mean	St. Dev	Median	Kurtosis	Skewness	Maximum	Minimum

SIR 5%	2.61%	0.04%	2.82%	-0.01	-0.37	10.71%	-9.15%
SIR 10%	2.10%	0.03%	2.25%	0.24	-0.37	11.55	-9.10%
SIR 90%	1.60%	0.06%	2.03%	0.26	-0.26	17.53%	-13.61%
SIR 95%	1.68%	0.06%	2.06%	0.08	-0.38	16.22%	-14.46%
SIR 5% - SIR 95%	0.94%	0.03%	1.02%	-0.40	0.23	9.75%	-6.13%
SIR 10% - SIR 90%	0.5%	0.03%	0.31%	-0.21	0.31	8.18%	-5.98%

6. Empirical results

We present the results of the regression analysis based on the FF3M and FF5 models in two sub-sections. In particular, the findings of the static version of these asset pricing models are reported in sub-section 6.1, whereas sub-section 6.2 reports additional results of key factors of the dynamic version of these models based on a rolling window as well as recursive approach.

6.1 Static regression analysis

The empirical results based on the FF3M (Equation 1) are reported in Table 5. We see in column (1) that the *alphas*, which capture the average monthly return, range from 0.3 for the SIR 95% portfolio to 0.2 for the SIR 90% portfolio. On the other hand, the lightly shorted portfolios, that is SIR 5% and SIR 10%, perform better with average monthly abnormal returns ranging from 1.528 for the SIR 5% to 0.982 for the SIR 10%. These results are consistent with Boehmer et al. (2010) as average abnormal monthly returns are reported as positive and of the same size for lightly shorted portfolios. On the other hand, our results related to the highly shorted portfolios, that is SIR 90% and SIR 95%, are opposed to Boehmer et al. (2010)'s findings of negative abnormal returns: our findings report alpha coefficients of 0.19 and 0.285 respectively. This overperformance may very well be due to the fact that the US stock market has behaved as a bull market over the period 2010-2017, with generally ever-increasing stock prices. Finally, highly shorted portfolios perform worse on an *alpha* coefficient basis relative to the lightly shorted portfolios. Looking at the results in column (2 of Table 4 we observe that the heavily shorted portfolios have larger MKT premium *betas* than their lightly shorted counterparts: this means that the non-diversifiable risk of the former is higher in comparison to the latter. Column (3) of Table 4 shows us that the coefficients of the SMB premium for the highly shorted portfolios are almost five-fold larger in comparison to the lightly shorted portfolios. Thus, heavily shorted portfolios resemble small capitalisation firms that outperform big firms. Column (4) illustrates that both heavily and lightly shorted portfolios have positive coefficients on HML: these coefficients are larger for the latter in comparison to the former. Column (5) shows us that the coefficients on the WML premium are positive for both lightly and heavily shorted portfolios, although they are statistically significant in the case of heavily shorted portfolios. Moving on to the long-short portfolios (that is SIR 5% - SIR 95% and SIR 10% - SIR 90%), we can see in column (1) of Table 5 that the *alpha* of the SIR 5% - SIR 95% is greater in comparison to the SIR 10% - SIR 90%, with values of 1.234 and 0.783 respectively. As shown in column (2), both long-short portfolios hold negative and statistically significant MKT premium *betas* of -0.275 and -0.230 respectively. Again, this means that if either the SIR 5% - SIR 95% or SIR 10% - SIR 90% portfolios were to be added to an existing holding, returns would be boosted at the same time as undiversifiable risk being reduced. Boehmer et al. (2010) propose the strategy of going long on the least shorted stock portfolio and short on the most shorted stock portfolio, which can be modelled with the SIR 5% - SIR 95% portfolio. This was proposed by Boehmer et al. (2010) because of the negative *beta* and the large abnormal return: however, in accordance with our results, we do not propose that strategy. It is again worth noting that the long-short portfolios and long only portfolios cannot be compared directly due to the cost of shorting associated with borrowed stocks. However, even if we do consider the cost of borrowing, the long-short portfolios greatly underperform in comparison to the long only portfolios. This is likely due to the high cost of borrowing associated with some highly shorted stocks. Finally, the results presented in Table 5 demonstrate that the best performing portfolio by far is the SIR 5% portfolio, and it seems most viable to simply hold the SIR 5% portfolio (in fact, column (1) of Table 5 shows an abnormal return of 1.528 which is the highest in comparison to all other portfolios) and not to apply a short strategy on the other end. In Table 6 we present, for means of comparison, the findings based on the FF5 model. The model performs well with *alphas* in column (1) ranging from 0.26 to 1.606, which are in general much larger coefficients compared to the *alphas* of the FF3M presented in Table 5. Once again, the MKT premium coefficients are negative and statistically significant for both SIR 5% - SIR 95% and SIR 10% - SIR 90% portfolios (column (2) of Table 6) indicates an inverse relationship between *betas* and the long-short portfolios' returns). The estimated coefficients of the SMB premium presented in column (3) of Table 6 are slightly smaller compared to the size of the SMB premium coefficients of the FF3M model. Like the results of the FF3M, the SMB premium coefficients obtained with the FF5 are consistently negative for the SIR 5% - SIR 95% and SIR 10% - SIR 90% portfolios. All the *HML* premium coefficients reported in column (4) of Table 6 are positive, although only statistically significant for the SIR 5% and SIR 10% portfolios. These results are consistent with the findings of the FF3M presented in column (4) of Table 5. Surprisingly, the coefficients of the profitability *RMW* factor (column (5) of Table 6) are negative and statistically significant in all portfolios but SIR 5% - SIR 95% and SIR 10% - SIR 90%: this therefore suggests that there is a negative premium associated with profitability. The coefficients of the investment premium CMA are generally positive although none are statistically significant. Finally, the results presented with the FF5 are consistent with the findings of the FF3M, reinforcing the conclusion that the strategy proposed by Boehmer et al. (2010) is not applicable in relation to the data and period of analysis considered in our study.

Table 5: Fama-French Three Factor model with Momentum results

	(1)	(2)	(3)	(4)	(5)	(6)
	Alpha	MKT Premium	SMB Premium	HML Premium	WML Premium	R^2
SIR 95%	0.285	1.203***	1.104***	0.104	-0.280***	0.91
#114 Stocks	(0.230)	(0.065)	(0.106)	(0.103)	(0.07)	
SIR 90%	0.19	1.178***	1.083***	0.068	-0.242***	0.94
#227 Stocks	(0.163)	(0.046)	(0.076)	(0.073)	(0.055)	
SIR 5%	1.528***	0.928***	0.281***	0.256***	-0.026	0.81
#114 Stocks	(0.210)	(0.06)	((0.097)	(0.094)	(0.071)	
SIR 10%	0.982***	0.948***	0.237***	0.203***	-0.005	0.92
#227 Stocks	(0.130)	(0.037)	(0.061)	(0.058)	(0.044)	
SIR 5% - SIR95%	1.234***	-0.275***	-0.823***	0.153	0.254**	0.48
#171 Stocks	(0.299)	(0.085)	(0.138)	(0.134)	(0.101)	
SIR 10% - SIR 90%	0.783***	-0.230***	-0.845***	0.135	0.237***	0.66
#171 Stocks	(0.201)	(0.057)	(0.093)	(0.907)	(0.068)	

Notes. Standard errors of coefficient estimates are shown in parentheses. The asterisks indicate the usual significance levels: * - p-value < 0.10; ** - p-value < 0.05; *** - p-value < 0.01.

Table 6: Fama-French Five Factor model results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alpha	MKT Premium	SMB Premium	HML Premium	RMW Premium	CMA Premium	R^2
SIR 95%	0.26	1.195***	0.981***	0.173	-0.389**	0.032	0.89
#114 Stocks	(0.243)	(0.071)	(0.118)	(0.140)	(0.172)	(0.224)	
SIR 90%	0.185	1.167***	0.969***	0.151	-0.372***	-0.036	0.94
#227 Stocks	(0.173)	(0.05)	(0.084)	(0.10)	(0.123)	(0.160)	

SIR 5%	1.606***	0.889***	0.193**	0.213*	-0.380**	0.064	0.83
#114 Stocks	(0.205)	(0.06)	(0.1)	(0.118)	(0.145)	(0.189)	
SIR 10%	1.023***	0.927***	0.192***	0.166**	-0.2**	0.062	0.92
#227 Stocks	(0.129)	(0.037)	(0.063)	(0.074)	(0.091)	(0.119)	
SIR 5% - SIR95%	1.337***	-0.306***	-0.788***	0.04	0.009	0.033	0.45
#171 Stocks	(0.314)	(0.091)	(0.153)	(0.181)	(0.222)	(0.290)	
SIR 10% - SIR 90%	0.830***	-0.239***	-0.777***	0.015	0.171	0.099	0.62
#171 Stocks	(0.216)	(0.063)	(0.105)	(0.124)	(0.153)	(0.199)	

Notes. Standard errors of coefficient estimates are shown in parentheses. The asterisks indicate the usual significance levels: * - p-value < 0.10; ** - p-value < 0.05; *** - p-value < 0.01.

6.2 Dynamic regression analysis

Over our sample period, US equity market prices were affected by a significant number of events. For instance, the Federal Reserve (Fed) of the US executed different forms of quantitative easing monetary policies to address the economic problems created by the 2007-2009 global financial crisis. The first round of this quantitative easing was implemented between the last quarter of 2008 and the third quarter of 2009. Another round was introduced in the last quarter of 2010. A third round occurred in the third quarter of 2012 in response to the slow response of the US economy to the previous round of quantitative easing. The financial liquidity provided by the outstanding increase in the number of assets (mainly government bonds and corporate debt) purchased by the Fed, and the subsequent ultra-low interest rates, boosted equity valuation and therefore prices over the entire 2010s (Houston and Spencer, 2018). Thus, to extend our main results as presented in Section 6.1, we further investigated whether our findings were period specific or whether there were significant changes over time. To achieve this, we conducted a 24-month rolling regression analysis using the FF3M and the FF5 models. We also conducted a recursive regression analysis where the length of the window increases as new observations are added: in practical terms, we started with a 24-month initial window and increased this window one month at a time for each recursive regression to a maximum length of 90 months (the end of our dataset). We then reported the results of the regression analysis for both the *alpha* and *beta* coefficients across the sample period.[9] Results are presented in sub-sections 6.2.1 for the rolling windows analysis and 6.2.2 for the recursive analysis.

6.2.1 Rolling window regression results

Figure 1 shows the rolling regression *alphas* and *betas* using the SIR 95%, SIR 90%, SIR 10% and SIR 5% portfolios. Panel A of Figure 1 shows that lightly shorted portfolio *alphas* outperformed heavily shorted portfolio *alphas*. There is one exception in July 2014 when a convergence of *alphas* between the heavily and lightly shorted portfolios occurred. The reason behind this could be an added level of optimism in the market, leading to investors and speculators holding more long positions than usual. Towards the end of 2015 and the beginning of 2016, the *alphas* of the heavily shorted portfolio SIR 95% turned negative (as seen in Panel A of Figure 1), again highlighting their vast underperformance in relation to lightly shorted

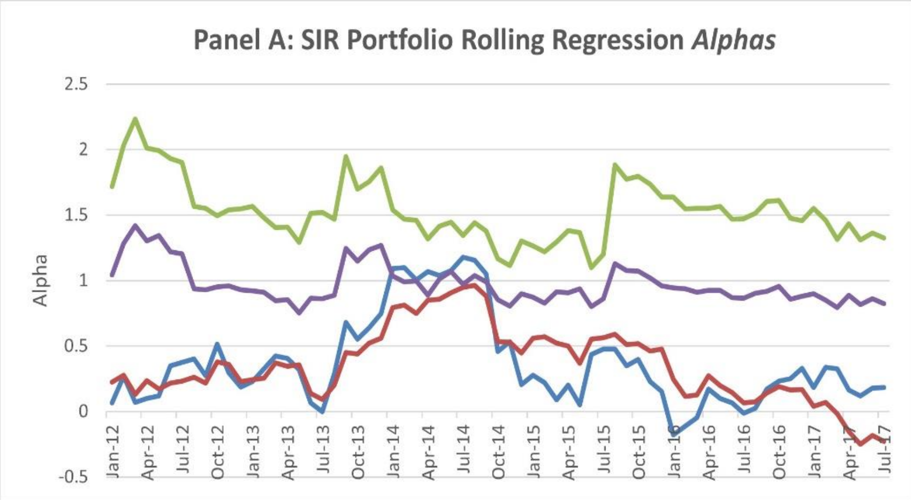
[9] These two factors are of interest as *alpha* is the excess return that the model is not able to explain, and *beta* is the market risk premium that is a key indicator of volatility with respect to the market.

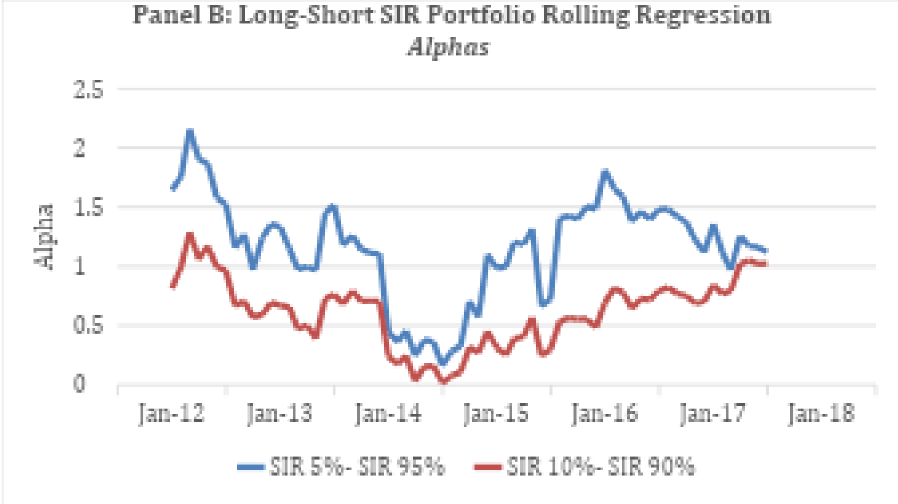
portfolios. Also, we can see that more short positions were being formed in anticipation of higher valuations and an overdue bear market which has not occurred since 2009.

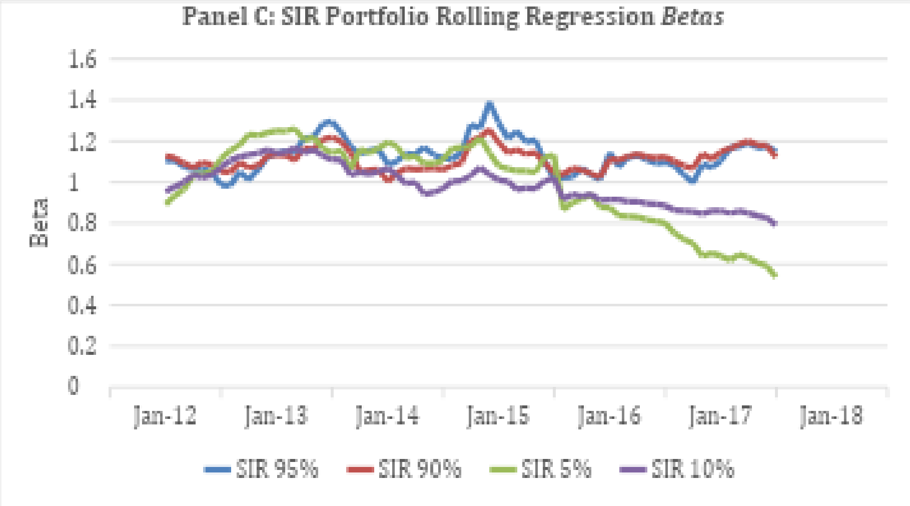
The range of *alphas* for the heavily shorted portfolios SIR 95% and SIR 90% is between -0.3 and 1.2, whereas the total range of *alphas* for the lightly shorted portfolio SIR 10% is between 0.8 and 2.2. Panel B of Figure 1 presents the rolling regression *alphas* calculated for the long-short portfolios SIR 5% - SIR 95% and SIR 10% - SIR 90%: the findings show that the SIR 5% - SIR 95% portfolios outperform the SIR 10% - SIR 90% portfolios in terms of abnormal returns over the study period. In both May 2014 and July 2014, the differences in terms of outperformance amongst the long-short portfolios was minimal. Overall, there is no point at which the SIR 5% - SIR 95% portfolios have a lower *alpha* than the SIR 10% - SIR 90% portfolios. Furthermore, after 2014, there were periods where the difference in abnormal returns between SIR 5% - SIR 95% and SIR 10% - SIR 90% was much larger than in the period up to 2014. The rolling regression *betas* using the SIR 95%, SIR 90%, SIR 10% and SIR 5% portfolios are shown in Panel C of Figure 1. Firstly, we can observe that since July 2015 there is a clear divergence in the *betas* of the lightly shorted portfolios (SIR 5% and SIR 10%) over the *betas* of the heavily shorted portfolios (SIR 90% and SIR 95%). This divergence indicates that lightly shorted portfolios become less volatile compared to heavily shorted portfolios. The rolling regression *betas* using the long-short SIR 5% - SIR 95% and SIR 10% - SIR 90% portfolios are shown in Panel D of Figure 1: the findings show that after July 2015 there is a noticeable drop in the *betas* of both the long-short portfolios. This may be linked to the fact that the *betas* of the lightly shorted portfolios decrease much more compared to the *betas* of the heavily shorted portfolios. Finally, the *betas* for the SIR 5% - 95% portfolio range from 0.22 to -0.61, whereas the range is from 0.7% to -0.35 for the SIR 10% - 90% portfolio: the difference in absolute values is larger in the case of the SIR 10% - SIR 90% in comparison to the SIR 5% - SIR 95% portfolio. This means that the volatility of the former was larger in comparison to the latter.

Figure 2 reports the *alphas* and *betas* rolling windows results by using the FF5 model. The average value of the *alphas* and *betas* are very similar in both FF3M and FF5 models. In relation to the *alphas*, the largest difference is between the SIR 5% - SIR 95% portfolios using the FF3M shows an average value of 1.162 whereas the average value for FF5 is 1.4. On the other hand, the smallest difference in terms of *alphas* is seen in the SIR 10% portfolio, with an average value of the *alpha* coefficient of 0.970 in the case of FFRM, and 1.036 for the FF5 model. Regarding the *betas*, the largest difference can be found again in relation to the SIR 5% - SIR 95% portfolio with average values of -0.135 in the case of FF3M and -0.247% in relation to the FF5 model. On the other hand, the smallest difference in absolute values was found between the SIR 5% with an average value of -0.994 for the FF3M and -0.954 for the FF5 model. Overall, the rolling window results of the FF5 are consistent with the findings of the FF3M.

Figure 1 - Fama and French Three Factor Model with Momentum: rolling windows results







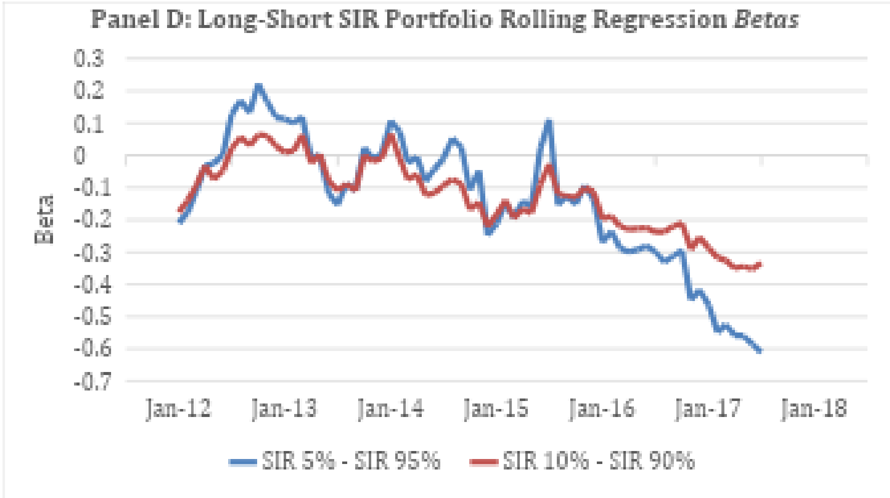
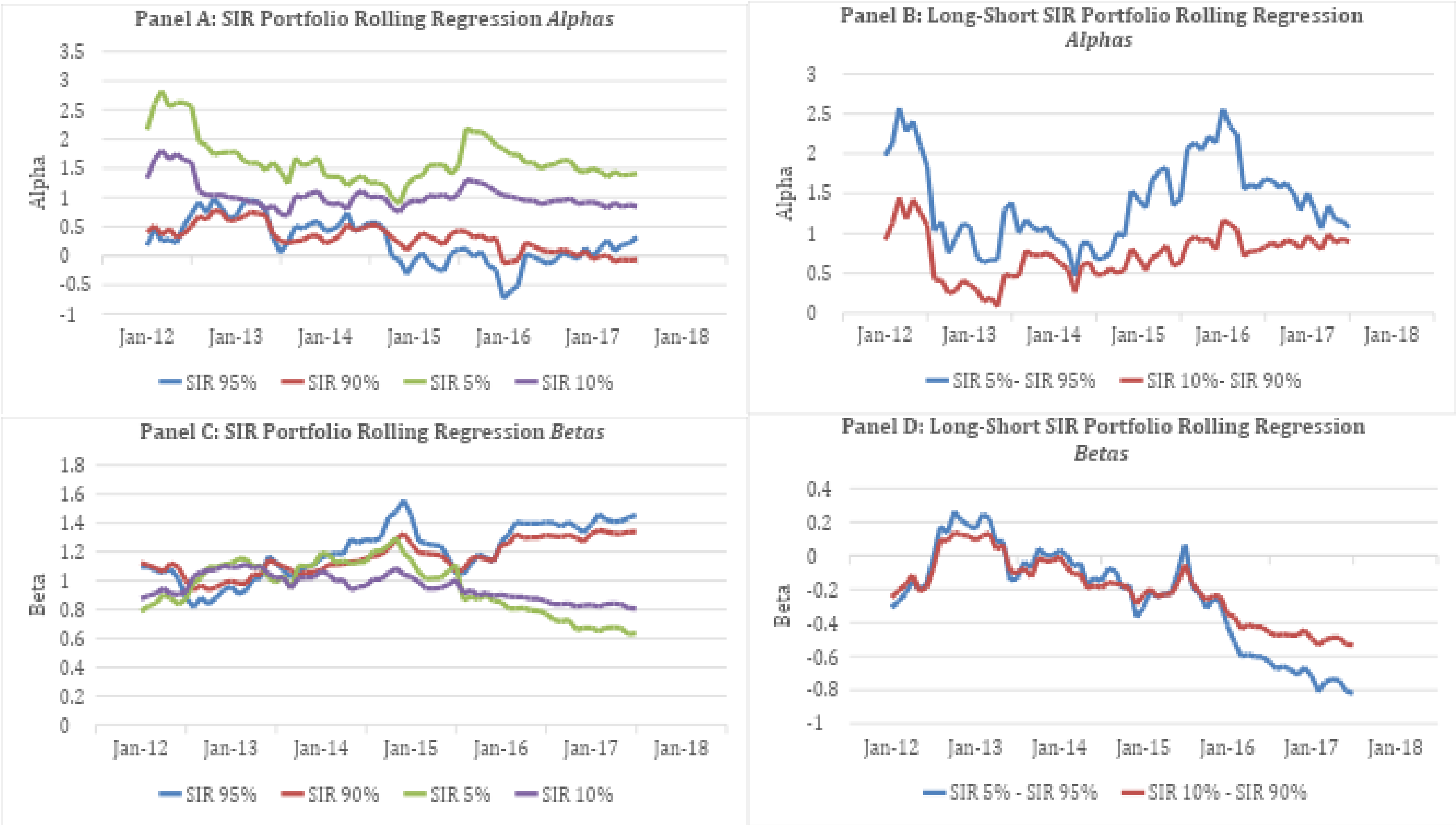


Figure 2 - Fama and French Five Factor Model: rolling windows results



6.2.2 Recursive regression results

Figure 3 presents the estimation of the recursive regression *alphas* using the FF3M for the SIR 95%, SIR 90%, SIR 10% and SIR 5% portfolios. Panel A shows that lightly shorted portfolio *alphas* outperform heavily shorted portfolio *alphas* over the entire period of analysis. Secondly, among the lightly shorted portfolios, the *alphas* of the SIR 5% outperform the SIR 10% with average values of 1.691 and 1.049 respectively. Thirdly, among the heavily shorted portfolios, the *alphas* of the SIR 95% consistently outperforms the *alphas* of the SIR 90% over the period January 2013 to October 2014. Panel B of Figure 3 shows that the SIR 5% - SIR 95% portfolio outperforms the SIR 10% - SIR 90% portfolio in terms of abnormal returns over the entire period of analysis. Interestingly, the *alphas* for the SIR 5% - SIR 95% portfolio ranged from 1.95 to 1.19, whereas the range was from 1.038 to 0.69 for the SIR 10% - SIR 90%: the difference in absolute values is larger in the case of the SIR 5% - SIR 95% meaning that the volatility of the SIR 5% - SIR 95% was greater in comparison to the SIR 10% - SIR 90%.

The recursive regression *betas* for the SIR 95%, SIR 90%, SIR 10% and SIR 5% portfolios are presented in Panel C of Figure 3.Similarly to the results of the rolling windows regression of the FF3M, all four portfolios' *betas* since the second half of 2014 demonstrate a clear divergence between the *betas* of the lightly shorted portfolios (SIR 5% and SIR 10%) and the *betas* of the heavily shorted portfolios (SIR 90% and SIR 95%). In other words, the *betas* for the lightly shorted portfolios tend to decline, whereas r in the highly shorted portfolios we observe the *betas* to increase: this divergence clearly indicates that highly shorted portfolios tend to become more volatile than the market compared to the lightly shorted portfolios. The recursive regression *betas* using the SIR 5% - SIR 95% and SIR 10% - SIR 90% portfolios are shown in panel D of Figure 4. A striking observation is that *betas* are negative for both portfolios over the entire period of analysis, indicating that the returns either in SIR 5% - SIR 95% or SIR 10% - SIR 90% portfolios and the benchmark (i.e. the market) move in opposite directions.

The recursive regression results based on the FF5 are presented in Figure 4 where we can observe that the trendlines of a*lphas* (Panels A and B) and b*etas* (Panels C and D) are very similar to the rolling windows trendlines of the FF3M reported in Figure 3. Secondly, by comparing the alphas across the alternative portfolios reported in Panel A and B of Figure 4, we can see that the SIR 5% is the portfolio with the greatest average *alpha* (1.832), whereas the portfolio with the smallest *alpha* is the SIR 90%. Overall, the recursive regression results of the FF5 are consistent with the findings of the recursive regression of the FF3M.

Figure 3 - Fama and French Three Factor Model with Momentum estimations: recursive regression results

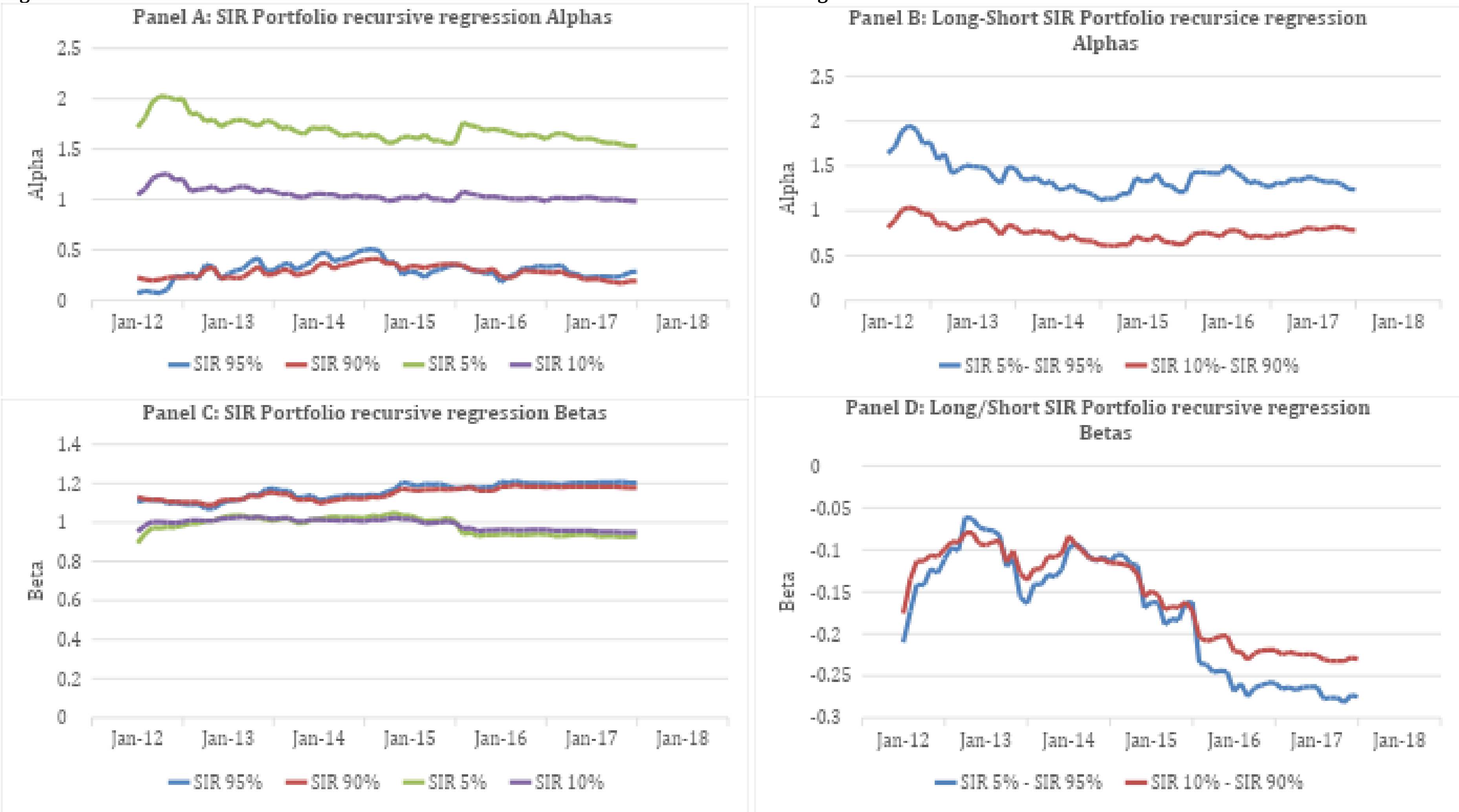
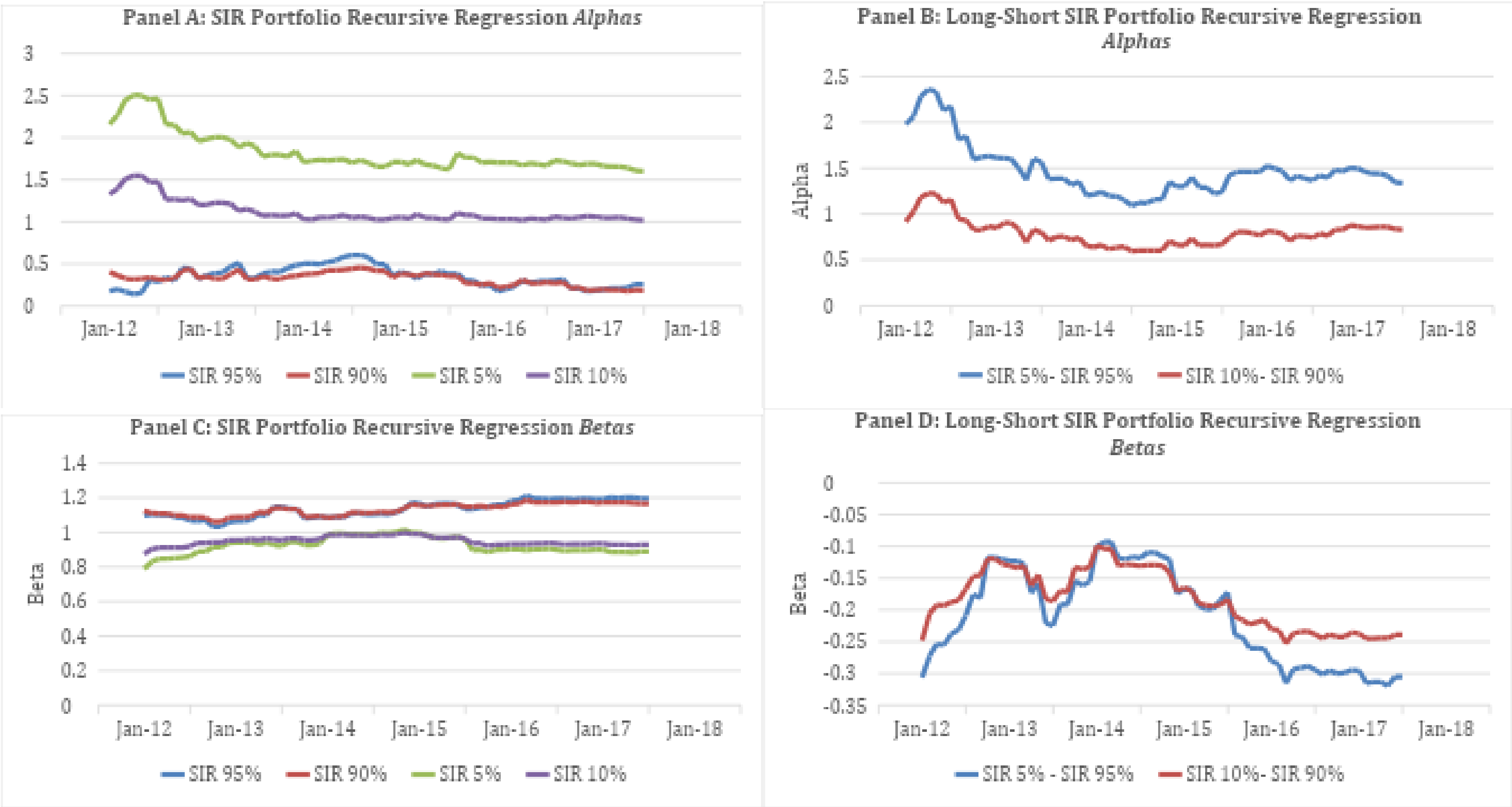


Figure 4 - Fama and French Five Factor Model estimations: recursive regression results



7. Summary and conclusion

In this study we investigated whether, after the publication of Boehmer et al. (2010), the strategy of going long on the least shorted stocks and going short on the most shorted stocks (with rebalancing each month on new short interest data) could be still valid or whether market participants had arbitraged this strategy so that it no longer holds true. This question helps contribute to the efficient markets debate: if a market is truly efficient, all known public information should be incorporated into the price of a security, and a strategy like this would have been made redundant.

By using the FF3M model, our results show that the SIR 5% are the portfolios with higher abnormal return (i.e. *alphas*) in comparison to all other either heavily shorted (SIR 90% and SIR 95%) or long-short portfolios (SIR 5% - SIR 95% and SIR 10% - SIR 90%). These findings are in line with the results of the FF5 model which we used for comparative purposes. Furthermore, the undiversifiable risk measured through the *betas* show that the SIR 95% portfolios are the ones with the higher *betas* in comparison to the SIR 5%, SIR 10% and SIR 90%: these results are the same for both the FF3M and FF5 models. More interestingly, the findings of the long-short portfolio shows that the market *betas* are negative for both SIR 5% - SIR 95% as well as SIR 10% - SIR 90%: this means that adding these portfolios to an existing holding would reduce the non-diversifiable risk.

The original strategy employed by Boehmer et al. (2010) was to hold a long position in a portfolio holding stocks with the least short interest, take a short position in a portfolio with stocks with the highest short interest and to rebalance each month. In our study, the outperformance of lightly shorted portfolio over heavily shorted portfolio is very evident. It is worth noting that it is difficult to compare long only portfolios with long-short portfolios owing to the borrowing costs associated with short selling. However, even accounting for marginal borrowing costs, our results show that the long-short portfolios vastly underperform the long SIR 5% portfolio. Therefore, our results clearly indicate that going long on the SIR 5% portfolio is advisable. This brings an element of redundancy to the strategy proposed by Boehmer et al. (2010) which recommends going short on stocks with the highest short interest for each month. This finding is backed by the fact that our results are similar in both the FF5 and FF3M models, therefore reinforcing the robustness of our conclusions.

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