US Sector Rotation with Five-Factor Fama-French Alphas

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Abstract

In this paper we investigate the risk-adjusted performance of US sector portfolios and sector rotation strategy using the alphas from the Fama-French five factor model. We find that five factor model fits better the returns of US sector portfolios than the three factor model, but that significant alphas are still present in all the sectors at some point in time. In the full sample period, 50% of sectors generate significant five-factor alpha. We test if such alpha signifies a true sector out/underperformance by applying simple long-only and long-short sector rotation strategies. Our long-only sector rotation strategy that buys a sector with a positive five-factor alpha generates four times higher Sharpe ratio than the S&P500 buy-and-hold. If the strategy is adjusted to switch to the risk-free asset in recessions, the Sharpe ratio achieved is ten-fold that of the buy-and-hold. The long-short strategy fares less well.

Key words: Fama-French Five Factor Model, US sectors, Performance, Sector Rotation

JEL code: G10, G11, G12

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1 Introduction and Background

Fama-French (1993) three-factor model (FF3 hereafter) and Carhart (1997) four-factor model have been used as standard pricing models and benchmark models for portfolio performance among both academics and practitioners. Fama and French (2015) five-factor model (FF5 hereafter) represents the newest addition to the multi-factor models that have been frequently used in empirical research, both in asset pricing and performance evaluation literature. Regardless of the frequent use of the FF3 model, there is evidence to suggest that it cannot completely explain the cross-section of stock returns[1]. Although FF3 model adjusts for outperformance tendency observed in original CAPM, academics question its ability to explain the cross-sectional variation in expected returns particularly related to profitability and investment (as seen in Chen et al., 2011; Aharoni et al., 2013; Novy-Marx, 2013; Walkshäusl and Lobe, 2014; Titman et al., 2004 among others). Motivated by this, Fama and French (2015) propose five-factor model which adds two additional factors, profitability and investment, to the FF3 model. They find that, for portfolios formed on size, book to market (B/M), profitability, and investment, the five-factor model provides a better fit than their original FF3 model.

In this paper, we investigate the risk-adjusted performance of US sector/industry portfolios in terms of the new FF5 model. The results from this segment of our research can be of particular interest to investors considering specialist sector funds. We further test whether the FF5 model alphas in the US sector portfolios can be exploited to formulate a profitable and feasible sector rotation strategy. The presence of sector ETFs makes sector investment strategies such as the one proposed in this paper attractive to practitioners and feasible at a reasonable level of transaction costs. The contribution of this paper to the literature is therefore two-fold: first, it adds to performance measurement literature by assessing US sector/industry performance within the new FF5 setting; and second, it adds to scarce sector investing literature with specific focus on a dynamic market-timing strategy – sector rotation. Sector rotation has received comparatively little attention from academics even though sector return predictability is well documented[2]. Being a dynamic strategy, sector rotation implies that investor switches their investment from one sector to another depending on the sector

[1] Some anomalies such as, positive relationship with momentum returns and earnings surprises, negative relationship with financial distress, net stock issues and asset growth, are left unexplained by Fama-French three factor model (see for example, Chen and Zhang, 2010; Fama and French, 2008, 1996; Cooper, Gulen and Schill, 2008; Daniel and Titman, 2006; Campbell, Hilscher and Szilagyi, 2008, etc)

[2] See for instance Beller, Kling and Levinson (1998)

outlook. Sector rotation studies differ, among other things, in indicators used to signal a switch from one sector to another. The signals range from economic indicators, technical indicators (such as relative strength indicator, widely used in technical analysis) and performance indicators such as alpha. We base this study on the following notion: if the FF5 alpha of a sector is indeed the true alpha (i.e. an accurate indicator of performance), then applying a sector investment strategy based on such alpha should generate higher return. To the best of our knowledge, this is the first study that applies the new Fama and French (2015) five-factor model as a benchmark model of sector performance and as a basis for US sector rotation strategy. Last, but not least, this paper aims to highlight the importance of sector/industry analysis for the investment process. Throughout the paper, we draw comparisons between Fama-French three and five-factor models' suitability for US sector returns and sector rotation strategy.

Let us first look at the existing evidence on sector performance. Most of the performance measurement literature focuses on the mutual funds, specifically long-only equity funds. The number of studies in this area is vast, see for instance Carhart (1997), Daniel (1997), Wermers (2000), Chen et al. (2000), Pástor and Stambaugh (2002) among others for US evidence. In contrast, much less attention in the literature has been given to the performance of the sector/industry investing. Dellva, DeMaskey and Smith (2001) study the timing and selection ability of 35 Fidelity sector mutual funds from the funds' inception till December 1998. The number of positive Jensen's alphas is 24-33 throughout subperiods, with the exception of 1994-1998 where the alphas declined to negative value. Faff (2004) tests the performance of 24 Australian industry portfolios and finds that there is a tendency for Mining and Resources sector to produce negative FF3 alpha, whereas Industrials tend to produce a positive one. In the US, Kacperczyk, Sialm and Zheng (2005) investigate the performance of industry concentrated mutual funds over the period January 1984 to December 1999. They argue that fund managers may deviate from the passive market portfolio by having their portfolio with specific industry concentration, and prove that funds that deviate more from the overall market by focusing on particular industries tend to perform better. Dou et al. (2014) study asset allocation in different economic regimes across sectors in the developed countries (North America, UK, Japan, and Europe). They report positive alpha of Energy, HiTech, and Health sectors; and negative alphas of Durable, Telecom, and Manufacturing sectors both in the bull market and the bear market. In this study, we will address the sector rotation taking into account different market states as well.

The success of sector rotation strategies was first documented by Sorensen and Burke (1986) and Grauer, Hakansson and Shen (1990). Switching sector based on mean-variance optimisation has shown to be a successful strategy in Beller, Kling and Levinson (1998). Fidelity Investments pushed sector investing into the mainstream by launching the slate of sector mutual funds referred as the “Select” series during the 1980s. However, the modern era of sector investing began in December 1998 when the first sector exchange-traded funds (ETFs) were introduced to equity investors. Based on the Fidelity Select Sector picking as a selection criteria, Sassetti and Tani (2006) use three simple sector rotation techniques, ranking sectors based on the Rate of Change, Alpha, and Relative Strength Indicator. They apply rotation strategy to 41 funds of the Fidelity Select Sector family from January 1998 to September 2003. Their findings show that a sector rotation based on the historical alphas appears more stable than the one using the Rate of Change. Their sector rotation strategy continuously outperforms buy-and-hold strategy. Conover et al. (2008) switch sectors according to macroeconomic conditions and find that their sector rotation strategy has infrequent rebalancing and consistent economically significant returns over the 33-year period in their study. Further, Chong and Philips (2015) find that a portfolio of sector ETFs constructed as a response of sectors to economic factors performs well relative to S&P 500 index. The outperformance of sector rotation strategy is also documented in the study of Shynkevich (2013) and Dou et al. (2014). The summary of the strategies used in the aforementioned sector rotation literature and their main findings can be found in Table A1 in the Appendix.

In this study, we use ten US Fama-French sector portfolios in the period 1964-2014 and our findings reveal that FF5 is a better model for describing sector returns than the FF3; containing additional information and having higher adjusted R-squared. FF5 is also statistically better fitted model and two additional factors (RMW and CMA) significantly increase the log-likelihood of the model. The sector rotation strategies in our study are in spirit most similar to Sassetti and Tani (2006). We follow one of their study’s main findings, which shows that alpha-based sector rotation provides more robust performance than that based on other indicators. Note, however, that Sassetti and Tani (2006) alpha estimation is based on the 30-, 60- and 90-*day* intervals. In the standard portfolio performance literature, to avoid the potential noise in the daily data, the alpha estimation is based on a monthly data and most commonly using a minimum of 36-months window, as in Cuthbertson et al. (2008) and Chinthalapati et al. (2017) among numerous other studies on performance. Hence, we develop a long-only and a long-short sector rotation strategy where a signal for switching is the FF5 factor model alpha. If the FF5 alpha for a sector in period t is positive (negative), we will buy (sell) that sector in period (t+1). Our sector rotation strategies are illustrated on both Fama-French US sector portfolios and the matching S&P Select Sector SPDR ETFs. In addition, we differentiate between recessions and expansions and devise additional long-only strategy, which buys a risk-free asset (US one-month Treasury Bill) if the economy is in recession.

Our long-only sector rotation strategy based on FF5 alphas outperforms the S&P 500 buy-and-hold benchmark strategy by 5.40% in terms of mean return and generates approximately four times higher Sharpe ratios. When we integrate business cycles into the trading strategy by taking a long position in the corresponding sectors with positive FF5 alpha during expansion period and in the one-month US T-bill during the recession period, the strategy generates 7.12% higher mean return of the S&P 500 benchmark and nearly 10 times higher Sharpe ratio. Our long-short strategy fares less well.

The paper is organised as follows: Section 2 describes the data and methodology, Section 3 presents the empirical findings of the study and Section 4 concludes the paper.

2. Data and Methodology

2.1 Data

We use monthly data of ten US sector portfolios obtained from Kenneth French's databank[3] from January 1964 to December 2014. The Ten sectors are Consumer Non-Durables (NoDur), Consumer Durables (Durbl), Manufacturing (Manuf), Energy (Enrgy), High Technology Business Equipment (HiTech), Telecommunications (Telcm), Shops, Health (Hlth), Utilities (Utils) and Other sectors[4]. Following Fama and French (1992), who argue that higher leverage of financial firms has a different meaning than for the non-financial firms (where high leverage indicates distress), we exclude financial sectors. S&P500 composite

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

[4] Each sector is composed of several industries as follows: portfolio of Consumer Non-Durables: Food, Tobacco, Textiles, Apparel, Leather, Toys; Consumer Durables: Cars, TV's, Furniture, Household Appliances; Manufacturing: Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Com Printing; Energy: Oil, Gas, and Coal Extraction and Products; High Technology Business Equipment: Computers, Software, and Electronic Equipment; Telecom: Telephone and Television Transmission; Shops: Wholesale, Retail, and Some Services (Laundries, Repair Shops); Health: Healthcare, Medical Equipment, and Drug; Utility and Others: Mines, Construction, Building Materials, Transport, Hotels, Bus Service, Entertainment and Finance industries.

index data is from DataStream. US business cycle data, which is used to define expansion and regression periods is from NBER[5].

In addition, we illustrate rotation strategies using a set of data a US sector investor is most likely to use nowadays: Select Sector SPDR ETFs. Those ETFs are not a perfect match for US Fama-French sector portfolios but we consider them a reasonable proxy that practitioners could use. By matching the industry definition of Fama-French sectors and Select Sector SPDR ETFs, we selected Consumer Discretionary (Durable), Consumer Staples (Non-durable), Energy, Health Care, Technology (HiTech) and Utilities sectors (6 sector ETFs) for trading illustration. Table A2 in the Appendix shows Fama-French and Sector Select SPDR ETF industry descriptions. Note that the component securities and the market capitalisation of Fama-French industry portfolios were not available to us, hence, in this study we use the correlation coefficients between Select Sector SPDR ETFs and Fama-French sector portfolio returns[6] to validate the degree of similarity between the comparable industry portfolios. The trading period when sector ETFs are used is shorter because of the availability of the data. The ETF data is obtained from DataStream and the trading period is from January 1999 to December 2014, providing 192 trading periods (months).

2.2 Methodology

2.2.1. Five-factor model alpha as a performance indicator and signal for sector rotation

Fama and French (2015) extended their previous three-factor model to five-factor model with the argument that the new five-factor model better describes the cross-section of returns. They add the two new factors, namely profitability (RMW) and investment (CMA) with their previous Market risk premium, Size (SMB), and Value (HML) factors:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}\left(R_{mt} - r_{ft}\right) + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t + \beta_{iCMA} CMA_t + \varepsilon_{it} \qquad \text{..........................(1)}$$

[5] http://www.nber.org/cycles.html

[6] Correlation coefficients between Select Sector SPDR ETFs and Fama-French sector portfolio return are: 0.828764862 (Consumer Staples/ Non-Durable), 0.816122412, (Consumer Discretionary/ Durable), 0.961186564 (Energy), 0.973998282 (Technology/HiTech), 0.705727311 (Health), 0.855138977 (Utilities).

Here, $(R_{it} - r_{ft})$ is excess return of sector i over the risk-free rate r_{ft} (proxied by one-month US Treasury bill); $(R_{mt} - r_{ft})$ is the market risk premium (*excess* return of the market defined as the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ minus one-month US Treasury bill); SMB is the difference between small cap and large cap firms that mimics the size risk. HML is the difference between high book-to-price and low book-to-market ratio; it mimics the value risk; RMW is the profitability factor which is the return spread of most profitable firms (Robust profitability) minus least profitable firms (Week profitability); CMA is the investment factor calculated as return spread of firms that invest conservatively minus those that invest aggressively. That is, RMW stands for robust minus weak profitability and CMA stands for conservative minus aggressive investment. The alpha of Fama-French five factor model $(\alpha_{i,t})$ denotes the access return that an active portfolio manager achieves above the expected return due to market, size, value, profitability and investment risk factors.

2.2.2. Sector Rotation Strategies and Buy-and-Hold

We apply a sector rotation strategy using as a signal for timing our allocations the rolling FF5 alphas of sector portfolios. The rolling FF5 alphas are estimated for the period January 1967 to December 2014.We use the first 36 months of the sample period to estimate the first set of alphas using the FF5 model. In total, there are 576 trading months. To begin with, we devise a long-only and a long-short strategy. Our long-only strategy takes the long position in month t+1 in all sector portfolios that have positive FF5 alpha for the 36 months rolling window ending in month t. The long-short rotation strategy buys sector portfolios in month t+1 that have positive alpha in month t and short-sells those with negative alpha in month t. We rebalance the position every month using the rolling window alpha of the previous 36 months. 36-months window for alpha estimation is selected as a standard in the recent finance literature, see for instance Cuthbertson et al. (2008) and Chinthalapati et al. (2017) among others. In addition, widely used Morningstar database computes performance measures such as alphas and Sharpe ratios based on a 36-months window[7]. The choice of monthly rebalancing is heuristic, similar to Sassetti and Tani (2006), as sector rotation is a dynamic market timing strategy. We do not claim that our choice of the alpha estimation period or the rebalancing frequency is optimal; it is simply used to explore the benefits of sector rotation based on five-factor alphas. Additionally, we incorporate economic recession

[7] https://web.stanford.edu/~wfsharpe/art/stars/stars2.htm

and expansion periods in our trading rule. In this strategy, we buy sectors with positive FF5 alpha in the expansion period and invest in the risk-free asset (one-month US T-bill) in recession periods. We use NBER US recession index to determine recession and expansion periods. We compare the Sharpe ratios of trading strategies with the Buy-and-Hold strategy that represents the investment in the S&P 500 index; a commonly used benchmark in performance evaluation literature.

2.2.3. Transaction costs

We report break-even transaction costs in this study. Those are the maximum costs per trade (deducted from the return generated in the month in which the trade has occurred) that one could pay so that the Sharpe ratio of the strategy breaks even (i.e. equalises with) the Sharpe ratio of the buy-and-hold. Note that each strategy has a number of trades/switches (in/out positions, so two switches denote one round-trip transaction) in each sector over the investment period. The expense ratio of Sector Select SPDR ETFs used in our trading strategies is 14bps per year[8] and an estimated average round-trip transaction cost (bid/ask spread) for the ETF trade is 25bps[9].

3. Empirical Findings

3.1. Descriptive statistics

Descriptive statistics (Mean Excess Return, Standard Deviation, Skewness and Kurtosis) of the ten sector Fama-French portfolios over the sample period are reported in Table 1.

All the sector portfolios have highly significant leptokurtic shape. Only Durables and Health sector has positive skewness. These distribution statistics indicate the probability of extreme values in the sector returns, most of the time they are on the left tail. The mean excess returns of 10 sector portfolios are similar with a minimum monthly return of 0.45% (Utility) and a maximum monthly return of 0.69% (Health). The Utility sector portfolio exhibits the lowest standard deviation, whereas HiTech sector is the riskiest.

[8] http://www.sectorspdr.com/sectorspdr/
[9] http://www.schwab.com/public/schwab/nn/articles/Copy-Of-ETFs-How-Much-Do-They-Really-Cost

Table 1: Descriptive Statistics

This table reports the descriptive statistics (Mean, Standard Deviation, Skewness and Kurtosis) of the 10 Fama-French sector portfolio returns (monthly excess returns) over the period January 1964 to December 2014. The values in the parentheses represent the p-values of Skewness-Kurtosis test for normality.

Sector Portfolio Excess Returns

	Mean Excess Return (%)	**Standard Deviation**	**Coefficient Of Skewness**	**Coefficient of Kurtosis**
NoDur	0.6820	4.3034	-0.3161*** (0.0016)	5.1108*** (0.0000)
Durbl	0.4561	6.3366	0.1592* (0.1058)	7.9030*** (0.0000)
Manuf	0.5724	4.9686	-0.4945*** (0.0000)	5.5911*** (0.0000)
Enrgy	0.6420	5.4176	-0.0081 (0.9340)	4.4112*** (0.0000)
HiTech	0.5702	6.5339	-0.2251** (0.0230)	4.2958*** (0.0000)
Telcm	0.4603	4.6470	-0.1894* (0.0549)	4.2634*** (0.0000)
Shops	0.6389	5.2272	-0.29187*** (0.0035)	5.4181*** (0.0000)
Hlth	0.6899	4.8708	0.0161 (0.8693)	5.5127*** (0.0000)
Utils	0.4504	4.0465	-0.1156 (0.2389)	4.0215*** (0.0002)
Other	0.5382	5.3302	-0.4858*** (0.0000)	4.8271*** (0.0000)

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

3.2. Performance of Sector Portfolios

Table 2 reports the mean of rolling FF5 alphas[10] and their standard deviations. The total number of alphas for each sector is 576. The highest average alphas are those of the HiTech and Healthcare sector, while the lowest negative ones are recorded for Durables (-24.99% p.a.). Across all 10 sectors, the average alpha is positive (3.15% p.a.). The positive average alpha is also reported in Dellva, DeMaskey and Smith (2001) for 35 Fidelity sector funds. However, their positive alpha is the average alpha of 35 sector funds, but they didn’t specify sectors with positive and negative alphas. Dou et al. (2014) use the MSCI data and report positive alpha of Energy, HiTech, and Health sectors; and negative alphas of Durable and

[10]We have also calculated rolling alphas for the same period using FF3 model. T-test shows that with the exception of Durables and Health sector, all other FF3 and FF5 mean rolling alphas are statistically different. This indicates that the FF5 and FF3 model convey different information to investor.

Manufacturing sectors both in bull market and bear market. Our findings in this paper are similar.

Table 2: Mean of Rolling FF5 Alphas

10 sector portfolios are regressed against Fama-French d 5 factors over the sample period January 1964 to December 2014 on a 36-months rolling window basis. The FF5 model is given as:

$$R_{it} - r_{ft} = \propto_{it} + \beta_{im}(R_{mt} - r_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \varepsilon_{it}$$

Here, Rmt (Market excess return), SMB (Small minus Big), HML (High minus Low Book-to-market), RMW (Robust minus week profitability) and CMA (Conservative minus Aggressive investment) are the factors of Fama-French models. Alpha is the performance unexplained by exposures to the given factors. Total number of alphas estimated for each sector is 576. The table reports the annualised mean of rolling FF5 alphas and standard deviation of FF5 rolling alpha series (in percentages) for each sector.

Sector	Mean (%)	Std. Dev (%)
NoDur	-6.12	41.42
Durbl	-24.99	2.34
Manuf	-5.03	1.53
Enrgy	6.69	3.06
HiTech	37.21	2.58
Telcm	-11.46	2.32
Shops	0.29	1.63
Hlth	37.73	1.76
Utils	6.41	1.90
Other	-9.20	1.27

To gain some insight into the performance of sectors over time, we plot the time series of rolling FF5 alphas of the ten sectors over the sample period, as per Figure 1. Health sector performs well during the late 60s and 70s. During the period 1979 to 1981 Energy sector provides higher alpha than any other sector, however, experienced powerful rebounds until end of 1986. We note the dominance of HiTech sector particularly during the period 1994 to 2003, which mostly coincides with the dot.com boom. We also observe that negative alphas of the Energy sector are more prominent than negative alphas of the other sectors. In the case of ‘Others’ sector, the FF5 alpha is negative over most of the sample period.

We further perform unpaired t-test to examine whether the FF5 model alphas are different across the sectors. Table 3 reports the unpaired t-test of the rolling window FF5 alphas of ten sector portfolios. 89% of FF5 alphas (40 out of 45 pairs) are found to be significantly different from each other at least at 10% level of significance[11].

[11] 39 out of 45 pairs are significant at 5% level of significance

Figure 1: FF5 Model Sector Alphas

This figure displays the time series of alphas that is obtained by regressing the sector portfolios with Fama-French 5 factors separately over the sample period January 1964 to December 2014 in 36 months rolling window basis.

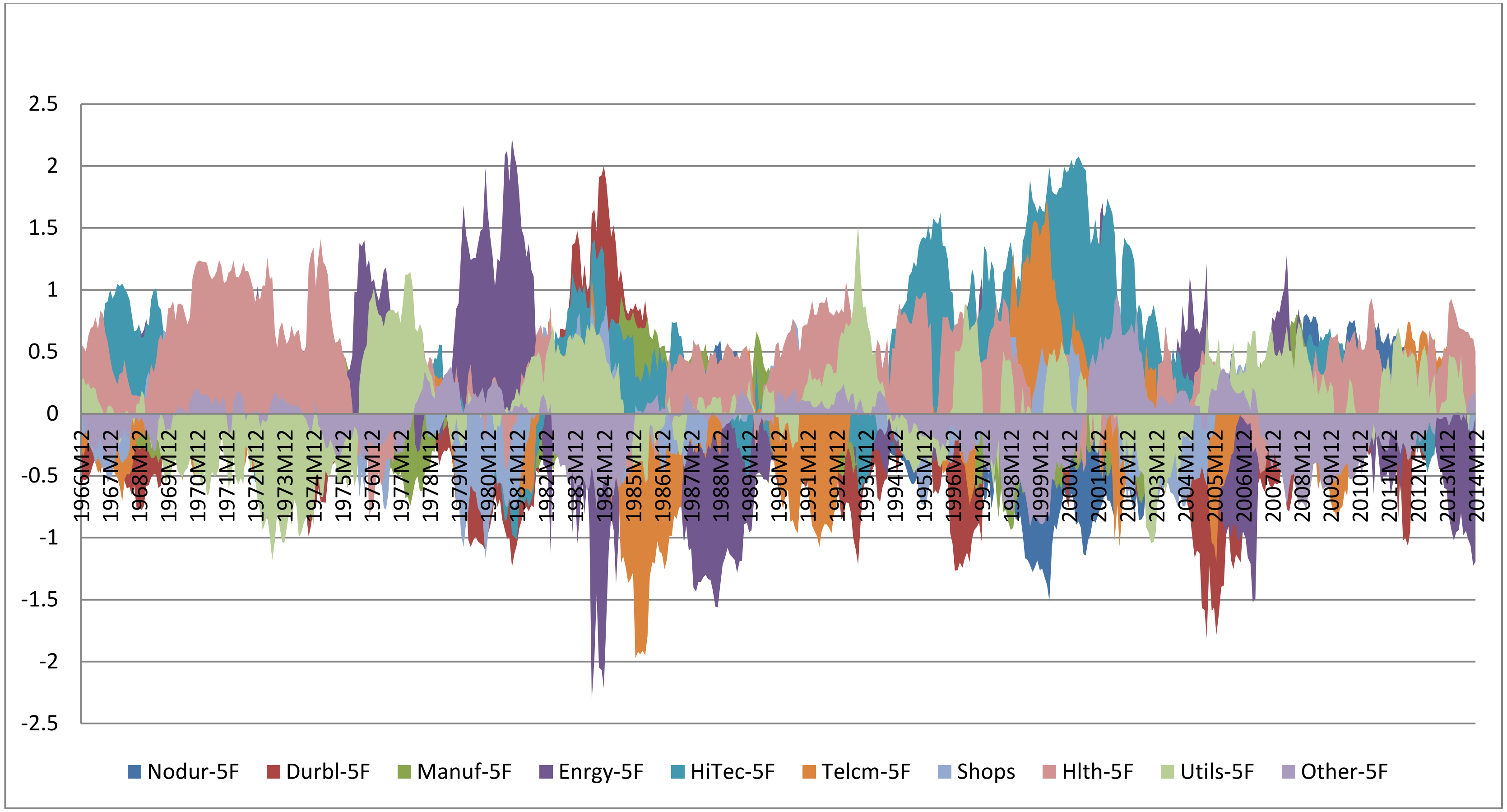


Table 3: P-value matrix of T-test for difference in Five-Factor Model Alphas across pairs of sectors

The FF5 alphas are obtained from the rolling window regression of ten sector portfolios with Fama-French five factors over the period January 1964 to December 2014. The mean of each sector alphas is within the parentheses of 1st row and 1st column. We perform t-test to check whether the mean sector alphas are different from each other. The table reports p-value matrix, which indicates the level of statistical difference between each pair of mean alphas. p-value of less than 0.1 indicates significance at 10% level.

	Nodur-5F (-0.0612)	Durbl-5F (-0.2499)	Manuf-5F (-0.0503)	Enrgy-5F (0.0669)	HiTech-5F (0.3721)	Telcm-5F (-0.1146)	Shops-5F (0.0029)	Hlth-5F (0.3773)	Utils-5F (0.0641)	Other-5F (-0.0919)
Nodur-5F (-0.0612)	-	0.0000	0.6353	0.0003	0.0000	0.0650	0.0069	0.0000	0.0000	0.1514
Durbl-5F (-0.2499)		-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Manuf-5F (-0.0503)			-	0.0006	0.0000	0.0208	0.0175	0.0000	0.0000	0.0365
Enrgy-5F (0.0669)				-	0.0000	0.0000	0.0650	0.0000	0.9376	0.0000
HiTech-5F (0.3721)					-	0.0000	0.0000	0.8681	0.0000	0.0000
Telcm-5F (-0.1146)						-	0.0000	0.0000	0.0000	0.3928
Shops-5F (0.0029)							-	0.0000	0.0145	0.0000
Hlth-5F (0.3773)								-	0.0000	0.0000
Utils-5F (0.0641)									-	0.0000
Other-5F (-0.0919)										-

For an illustration of comparison with FF5 alphas, we include now both the FF3 and Jensen's alphas. 577 regressions were completed per each portfolio and per each model, 17310 (=577x10x3) regressions in total. Table 4 reports the percentage of statistically significant or insignificant rolling alpha estimates under the three models (CAPM, FF3 and FF5), for each sector. Manufacturing, Energy and HiTech sectors have an increasing pattern of significant alphas when we move from one factor (Jensen's alpha) to FF5 alpha. In the case of the Manufacturing sector, the total significant alpha is 9.36% in case of CAPM, but it doubles when alphas are estimated by FF5. This is the sector where negative alphas increase the most - by 85%. We observe similar pattern the Energy and HiTech sector. In contrast, in the Telecom sector, the percentage of total significant FF5 alphas is lower than Jensen's alphas but higher than FF3 alphas. This is because the Telecom sector couldn't achieve many (significantly) positive alphas over the sample period, but the percentage of negative alphas in this sector has increased. This corroborates (under)performance of Telecom sector reported in Figure 1, where the time series of FF5 alpha is negative over most of the period. For the Utility sector, the significant FF5 alpha is marginally lower than the FF3 one, although the percentage of positive (negative) alpha is higher (lower) than in FF3.

In summary, a significant percentage of sectors appear to have both significantly positive and significantly negative alphas in case of CAPM, FF3 and FF5. Some of the alphas lose their significance (6 out of 10 sectors) when additional factors are included in the model. Undeniably, overall positive alpha has decreased for 9 out of 10 sector portfolios when we move from FF3 to FF5 model, while this amount is 8 out of 10 when we move from CAPM to FF5 model. If the FF5 alphas are comparatively more 'true' than their predecessors, then they should be exploitable in the context of sector investing. We will illustrate this on the example of sector rotation strategies.

Ultimately, we use the adjusted R-squared as the means of comparison between FF3 and FF5 models. The average adjusted R-squared for each sector (also reported in Table 4) is always higher for FF5 model. This corroborates that using the two additional factors (CMA and RMW) in the FF5 model enhances the explanatory power of the model when it comes to sector returns.

Table 4: Significance of Alphas over the Rolling Window

This table reports the significance of 10 sector portfolio alphas for both the three-factor and five-factor model at 90% confidence, based on the two-tailed test. Jensen Alpha is also reported for illustration purpose. We regress the sector portfolios with one factor (market), three factors and five factors separately over 36 months rolling window (577 regression for each portfolio); and count the number of times the alphas are significant, positively significant, negatively significant, positive, or negative. The percentage of sectors with statistically significant and insignificant coefficient estimates under the models (CAPM, Fama-French 3F and Fama-French 5F are reported. Average adjusted R-squared for each sector portfolio and each model are reported in the last column.

Sectors		Significant			Overall (total)		Adjusted Average R-Squared
		Positive	Negative	Total	Positive	Negative	
NoDur	Jensen Alpha	26.34%	0.87%	27.21%	74.00%	26.00%	70.42%
	3F Alpha	20.28%	3.81%	24.09%	72.62%	27.38%	75.73%
	5F Alpha	4.68%	5.20%	9.88%	46.27%	53.73%	79.19%
Durbl	Jensen Alpha	1.04%	10.75%	11.79%	37.95%	62.05%	66.30%
	3F Alpha	3.29%	9.71%	13.00%	26.86%	73.14%	73.27%
	5F Alpha	2.60%	9.88%	12.48%	23.74%	76.26%	74.33%
Manuf	Jensen Alpha	6.76%	2.60%	9.36%	50.61%	49.39%	87.25%
	3F Alpha	6.59%	7.45%	14.04%	49.22%	50.78%	88.87%
	5F Alpha	10.57%	8.15%	18.72%	36.22%	63.78%	89.52%
Enrgy	Jensen Alpha	4.68%	2.43%	7.11%	69.15%	30.85%	43.86%
	3F Alpha	8.32%	2.95%	11.27%	57.89%	42.11%	53.10%
	5F Alpha	10.92%	7.80%	18.72%	57.02%	42.98%	59.30%
HiTech	Jensen Alpha	5.03%	8.84%	13.86%	42.63%	57.37%	75.66%
	3F Alpha	16.64%	2.95%	19.58%	57.54%	42.46%	83.76%
	5F Alpha	23.05%	1.21%	24.26%	71.75%	28.25%	85.52%
Telcm	Jensen Alpha	12.48%	4.85%	17.33%	59.62%	40.38%	54.98%
	3F Alpha	7.11%	2.25%	9.36%	47.83%	52.17%	59.01%
	5F Alpha	2.95%	7.97%	10.92%	37.09%	62.91%	60.91%
Shops	Jensen Alpha	21.66%	5.55%	27.21%	58.23%	41.77%	73.01%
	3F Alpha	13.52%	2.25%	15.77%	63.08%	36.92%	76.89%
	5F Alpha	6.93%	2.60%	9.53%	50.43%	49.57%	79.57%
Hlth	Jensen Alpha	14.73%	1.21%	15.94%	67.94%	32.06%	59.96%
	3F Alpha	21.49%	0.00%	21.49%	89.25%	10.75%	67.42%
	5F Alpha	20.45%	0.00%	20.45%	77.99%	22.01%	68.70%
Utils	Jensen Alpha	11.79%	1.21%	13.00%	67.07%	32.93%	37.12%
	3F Alpha	4.51%	1.21%	5.72%	48.01%	51.99%	52.15%
	5F Alpha	3.29%	0.87%	4.16%	57.02%	42.98%	56.08%
Other	Jensen Alpha	5.55%	7.11%	12.65%	51.30%	48.70%	86.79%
	3F Alpha	0.17%	14.90%	15.08%	27.21%	72.79%	91.77%
	5F Alpha	1.56%	9.19%	10.75%	43.67%	56.33%	92.21%

From the analysis that has been done so far in this study, it is observed that the risk-adjusted performance of sector portfolios in terms of one- or three-factor model is different to that of the five-factor model. The significant difference between the time series of FF3 and FF5 alphas indicates that they convey different information.

Table 5 and Table 6 report the Ordinary Least Square (OLS) estimates of the three-factor model and five-factor model respectively for our ten sector portfolios for the full sample period January 1964 to December 2014. The tables report the average alphas, factor betas and adjusted R-squared of the regressions. In the case of FF3 (Table 5), 50% of sector alphas is significantly different from zero. Only two sectors (Durables & Others) show significant underperformance after adjusting for market, size and value factors; while three sectors show significant outperformance (Non-durables, Hi-Tech and Health). Almost all of the betas are found to be significant.

Table 6 shows similar results. According to FF5 model alpha, Durables, Manufacturing and ‘Others’ significantly underperform by 0.45%, 0.16%, and 0.23% respectively, after adjusting for market, size, value, profitability and investment risk. Similar to FF3, FF5 also shows 50% significant non-zero sector alphas. With the exception of the Non-durable sector, the alphas that are significant in FF3 remain significant in FF5 model. It also can be observed that, apart from HiTech, the significant alphas in the FF5 are lower than those of FF3. This might indicate that FF5 captures some of the unsystematic risk that FF3 cannot capture leaving less exploitable return for active managers. Moreover, the adjusted R-squared of FF5 is higher than that of FF3 for each of the ten sectors. This clearly shows a better fit of FF5 model to the sector portfolios. Hence from the statistical point of view, we can argue that in an unconditional setting Fama-French five-factor model is more accurate for sector pricing than their previous three-factor model. However, the significant alphas indicate that, there are some returns left unexplained beyond the exposures to Market, Size, Value, Profitability, and Investment factors and that they can be exploited.

In model diagnostics, we perform redundant variables test to check the statistical significance of two additional factors (RMW and CMA) in FF5 Model. We use a Likelihood ratio test that assumes FF3 model is a nested model of FF5 model, and hypothesise that the variable of interest has zero coefficient and might thus be deleted from the equation. The test statistics of redundant variables test (F-statistic) has an exact finite sample F-distribution under the null hypothesis. Panel A of Table 7 consist the results of redundant variables (Likelihood ratio) test under the null hypotheses: $H_{01}: \beta_{RMW} = 0; H_{02}: \beta_{CMA} = 0;\ H_{03}: \beta_{RMW} = \beta_{CMA} = 0$. We can observe that, eight out of ten portfolios exhibits significant profitability beta whereas five out of ten portfolios exhibit significant investment betas. Both profitability and investment factor are jointly significant in all but one portfolio (Energy).

It is a custom to believe that aggregate shocks such as business cycles will cause a structural break in a time-series. A structural change in second moments will produce a change in asset betas that might result in a spuriously significant alpha, (Turtle and Zhang, 2015). During model diagnostics, we check whether there is a structural change in the Fama-French asset pricing models due to the business cycles; with an intention to derive trading strategies accordingly. In this manner, we perform Factor Breakpoint test that splits an estimated equation's sample into a number of subsamples classified by one or more variables and examines whether there are significant differences in equations estimated in each of those subsamples. The Wald statistics in the Panel B of Table 7 indicates that both FF3 and FF5 models exhibit structural changes due to business cycles; FF5 differing more significantly than FF3 between economic states. Given these results, we will develop a trading strategy that incorporates business cycles with a potential of generating better performance.

Table 5: Regression of 3 Factor model with 10 sector portfolios

This table reports the Ordinary Least Square estimates of 10 sector portfolios by Fama-French three-factor model (FF3) over the sample period January 1664 to December 2014.The FF3 is expressed as:
$R_{it} - r_{ft} = \propto_{it} + \beta_{im}(R_{mt} - r_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \varepsilon_{it}$
Here, Rmt (Market excess return), SMB (Small minus Big), and HML (High minus Low Book-to-market) are the factors of Fama-French models. Alpha (intercepts) is the average returns, expressed in percentage, unexplained by exposures to the Rmt, SMB, and HML. The values in the parentheses represent the p-values.

Sector Portfolio	**Alpha**	**Market Beta**	**SMB Beta**	**HML Beta**	**Adjusted R^2**
NoDur	0.2088** (0.031)	0.8420*** (0.000)	-0.0381 (0.234)	0.1704*** (0.000)	70.53%
Durbl	-0.3915*** (0.006)	1.2134*** (0.000)	0.1587*** (0.001)	0.5353*** (0.000)	70.56%
Manuf	-0.0379 (0.582)	1.0701*** (0.000)	0.0285 (0.2113)	0.1808*** (0.000)	88.74%
Enrgy	0.1453 (0.374)	0.8974*** (0.000)	-0.2154*** (0.000)	0.2975*** (0.000)	46.85%
HiTech	0.1916* (0.098)	1.0935*** (0.000)	0.2039*** (0.000)	-0.6286*** (0.000)	81.61%
Telcm	0.0567 (0.649)	0.8391*** (0.000)	-0.2046*** (0.000)	0.1128*** (0.012)	57.90%
Shops	0.0907 (0.402)	0.9880*** (0.000)	0.1391*** (0.000)	0.0363 (0.348)	74.95%
Hlth	0.4430*** (0.000)	0.8265*** (0.000)	-0.2404*** (0.000)	-0.2741*** (0.000)	62.54%
Utils	0.0062 (0.960)	0.6550*** (0.000)	-0.1785*** (0.000)	0.4593*** (0.000)	45.84%
Other	-0.2019*** (0.004)	1.1658*** (0.000)	0.0670*** (0.004)	0.3766*** (0.000)	89.96%

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

Table 6: Regression of 5 Factor model with 10 sector portfolios

This table reports the Ordinary Least Square estimates of 10 sector portfolios by Fama-French five-factor model (FF5) over the sample period January 1964 to December 2014.The FF5 is expressed as:
$R_{it} - r_{ft} = \propto_{it} + \beta_{im}(R_{mt} - r_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \varepsilon_{it}$
Here, Rmt (Market excess return), SMB (Small minus Big), HML (High minus Low Book-to-market), RMW (Robust minus week profitability) and CMA (Conservative minus Aggressive investment) are the factors of Fama-French models. Alpha (intercepts) is the average returns unexplained by exposures to the Rmt, SMB, HML, RMW and CMA. The values of alpha are in percentage.
The values in the parentheses represent the p-values.

Sector Portfolio	**Alpha**	**Market Beta**	**SMB Beta**	**HML Beta**	**RMW Beta**	**CMA Beta**	**Adjusted R^2**
NoDur	-0.0842 (0.325)	0.9103*** (0.000)	0.1029*** (0.000)	-0.0124 (0.760)	0.6310*** (0.00)	0.3949*** (0.00)	78.43%
Durbl	-0.4545*** (0.002)	1.2245*** (0.000)	0.1987*** (0.000)	0.5239*** (0.000)	0.1754** (0.016)	0.0215 (0.839)	70.76%
Manuf	-0.1643** (0.014)	1.0953*** (0.000)	0.1010*** (0.000)	0.1357*** (0.000)	0.3203*** (0.000)	0.0938** (0.051)	90.23%
Enrgy	0.0980 (0.562)	0.9155*** (0.000)	-0.2116*** (0.000)	0.2128*** (0.008)	0.0235 (0.780)	0.1887 (0.122)	46.89%
HiTech	0.4224*** (0.000)	1.0306** (0.000)	0.1175*** (0.003)	-0.4130*** (0.000)	-0.3953*** (0.000)	-0.4736*** (0.000)	83.30%
Telcm	0.1491 (0.238)	0.8273*** (0.000)	-0.2754*** (0.000)	.09419 (0.116)	-0.3076*** (0.000)	0.0484 (0.596)	59.64%
Shops	-0.1080 (0.291)	1.0233*** (0.000)	0.2644*** (0.000)	-0.0018 (0.970)	0.5502*** (0.000)	0.0732 (0.322)	79.08%
Hlth	0.2533** (0.041)	0.8732*** (0.000)	-0.1558*** (0.000)	-0.4117*** (0.000)	0.3807*** (0.000)	0.2999*** (0.001)	64.80%
Utils	-0.0148 (0.908)	0.6653*** (0.000)	-0.1828*** (0.000)	0.4042*** (0.000)	-0.0143 (0.822)	0.1233 (0.181)	45.86%
Other	-0.2258*** (0.001)	1.1605*** (0.000)	0.1076*** (0.000)	0.4463*** (0.000)	0.1717*** (0.000)	-0.1597*** (0.002)	90.67%

* **Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

Table 7: Model Diagnostics

This table reports the Likelihood Ratio test and Wald Test for Factor Break Point for the corresponding hypothesis. We perform likelihood ratio test for the redundant variables to identify the significance of the two added factors (RMW and CMA) in the Fama-French FF5. We also perform the Factor Break Point test to examine whether the subset of parameters differs due to the business cycles (BC). The test statistics is computed from a standard Wald test of the restriction that the coefficients on the equation parameters are the same in all subsamples. The Factor Breakpoint test splits an estimated equation's sample into a number of subsamples classified by one or more variables and examines whether there are significant differences in equations estimated in each of those subsamples. A significant difference indicates a structural change in the relationship. The p-value of Wald test and Likelihood Ratio test indicates the probability of the insignificance of corresponding regressor.

	NoDur	**Durbl**	**Manuf**	**Enrgy**	**HiTech**	**Telcm**	**Shops**	**Hlth**	**Utils**	**Other**
Panel A: Likelihood Ratio Test for Redundant Variable										
$H_{01}: \beta_{RMW} = 0$	220.0168*** (0.0000)	5.7850** (0.0165)	93.8751*** (0.0000)	0.0784 (0.7795)	48.3847*** (0.0000)	23.9610*** (0.0000)	116.9313*** (0.0000)	38.3021*** (0.0000)	0.050946 (0.8215)	24.53581 (0.0000)***
$H_{02}: \beta_{CMA} = 0$	40.8665*** (0.0000)	0.0413 (0.8391)	3.8220* (0.0510)	2.3927 (0.1204)	32.9377*** (0.0000)	0.2814 (0.5940)	0.9815 (0.3222)	11.2710*** (0.0008)	1.796862 (0.1806)	10.07030 (0.0016)***
$H_{03}: \beta_{RMW} = \beta_{CMA} = 0$	112.2745*** (0.0000)	3.0312** (0.0490)	47.3725*** (0.0000)	1.2130 (0.2945)	31.6660*** (0.0000)	14.1011*** (0.0000)	61.0811*** (0.0000)	20.4472*** (0.0000)	1.108467 (0.3307)	23.99183 (0.0000)***
Panel B: Factor Break Point Test										
Structural change due to BC (FF5)	7.5203 (0.2754)	5.9712 (0.4264)	9.5444 (0.1452)	36.9510*** (0.0000)	11.1681* (0.0833)	8.2301 (0.2217)	23.5365*** (0.0000)	9.3835 (0.1531)	25.95887 (0.0002)***	9.007625 (0.1731)
Structural change due to BC (FF3)	16.0655*** (0.0029)	5.9624 (0.2020)	10.5225** (0.0325)	35.2219*** (0.0000)	7.8421* (0.0975)	10.4302** (0.0338)	22.0615*** (0.0002)	11.3597** (0.0228)	15.82159 (0.0033)***	12.72868 (0.0127)**

***Implies the significance at 1% level of significance.
** Implies the significance at 5% level of significance.
*Implies the significance at 10% level of significance.

3.3. Sector Rotation Strategy

Given the results from the previous section, which show better fit of the five-factor model to US sector returns (higher adjusted R-squared compared to FF3 and CAPM), we will proceed in this section using the five-factor model as a basis for our trading strategy. Sorensen and Burke (1986) argue that application of a sector rotation strategy requires at least two assumptions. First, we must assume that sector-specific effects cause price movements to differ from one group to another. We have shown earlier in this paper that five-factor alphas overall differ between sectors (see Table 3). Second, sector rotation assumes that the firms within a sector exhibit some homogeneity in their relative price movements, aside from overall market influences. Intuitively, companies in the same sector or industry would exhibit higher pairwise return correlations than companies from different industries. Firms within the same industry that operate under the same regulatory environment are likely to react similarly to technological innovations, and also exhibit similar sensitivity to macroeconomic shocks and/or government policy. These firms are also likely to be exposed equally to the fluctuations in the supply & demand or across the consumer-supplier chain of their corresponding market. We hypothesised that, if the FF5 model produces true alpha then these rolling alphas can be used in sector rotation strategies.

Note that the trading strategies we use in this paper are for illustration purpose only. It is not the aim of this paper to identify the best or most optimal strategy to trade upon. We first illustrate sector rotation using Fama-French US sector portfolios, but the strategy can be replicated (relatively) cheaply by using US sector ETFs. We demonstrate replication through ETFs later in this study.

Table 8 provides the annualised returns, standard deviation, and Sharpe ratios of long-only and long-short sector rotation strategies. For comparison, the table reports results of rotation based on both FF5 and FF3 models. Although our strategies with both FF3 and FF5 rolling alphas significantly outperform the benchmark, we observe that there is no considerable difference in the profitability of the strategies driven by FF3 and FF5 models, in spite of the fact that FF5 is statistically superior when it comes to sector returns. Given that Fama-French sector portfolios are not tradable, we will examine how the comparable sector ETF trading based on FF5 alphas fares with that based on FF3 alphas in the next section. Table 8 also shows that long-only based sector rotation trading provides nearly double the buy-and-hold return of S&P 500 with similar standard deviation. Sharpe ratio of long-only rotation is approximately four times higher (0.12) than the Sharpe ratio of the S&P 500 (0.03). Long-short strategy underperforms the benchmark.

Sorensen and Burke (1986) argue that any benefits of sector rotation may depend on existing market conditions irrespective of the particular analytical approach. We test their claims by splitting the trading periods according to the NBER business cycles. Factor Breakpoint test due to business cycles (Table 7) also suggest the possibility of more accurate trading and generate higher return by incorporating business cycles in the trading strategies. The trading strategy where we buy corresponding sectors with positive FF5 alpha in the expansion period otherwise invest in risk-free asset, generates the superior returns. The returns are more than 7% higher than the buy-and-hold return of S&P 500 with at least 2% lower risk (standard deviation). Even more pronounced than in the long-only trading, the Sharpe ratio of the long-only strategy that accounts for recession is around five times higher than that of the buy and hold of the S&P 500 index.

Table 8: Trading with alphas

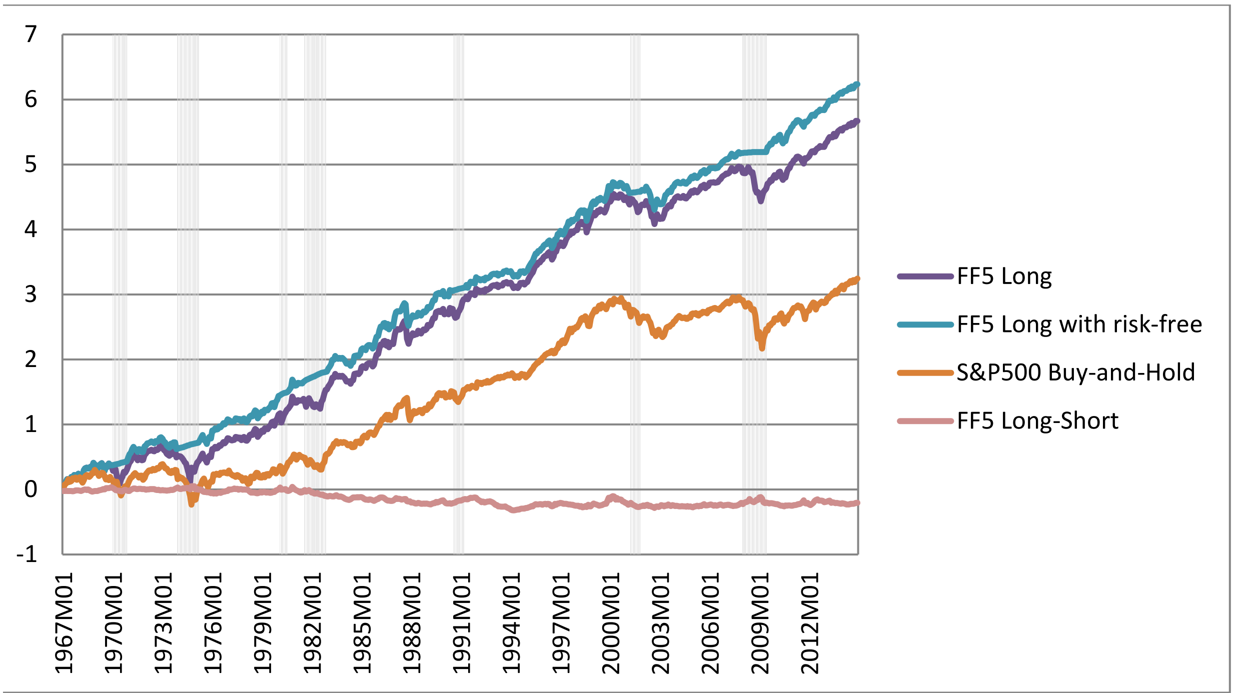
This table reports the annualised Mean return, Standard Deviation and Sharpe Ratio of long-only and long-short sector rotation strategies with FF5 rolling window alphas. The buy-and-hold strategy represents the investment in the S&P 500 index. Rotation strategies take long position in the sector portfolios that have positive alpha of 36 months rolling window regression. Another rotations strategy incorporates business cycles and take long position in the sector portfolios that have positive alpha of 36 months rolling window regression, however during recession it invests in one-month US T-Bill. The Long-Short rotation strategies buy sector portfolios that have positive alpha and sell those with negative alpha. We used NBER recession index to calculate the return in recession and expansion period. Mean returns and standard deviations (Std. Dev.) have been annualised. The table reports trading results based on FF5 and FF3 alphas for comparison.

Trading Strategy	Mean Return	Std. Dev	Sharpe Ratio
Long Only based on FF5 alpha	11.07%	15.83%	0.12462
Long Only based on FF3 alpha	11.20%	15.54%	0.1283
Long –Short based on FF5 alpha	-0.52%	4.39%	-0.3465
Long –Short based on FF3 alpha	-0.29%	4.69%	-0.3110
Long Only with risk-free asset in Recession (FF5)	12.79%	13.24%	0.17462
Long Only with risk-free asset in Recession (FF3)	12.88%	13.02%	0.1786
Buy & Hold S&P 500	5.67%	15.51%	0.0333

The superior performance of the sector rotation strategies based on FF5[12] can be seen in Figure 2, which displays cumulative return of the strategies and buy and hold of the S&P 500 index. The cumulative return of the sector rotation strategies over buy and hold grows over time. Specifically, if we compare long-only trading (FF5 long) and trading that incorporates business cycles (FF5 long with risk-free), we can observe that trading strategy that invests in T-bills during the recession has the 72 BPS higher return compared to the long-only sector rotation that does not account for the business cycles. It also increases the Sharpe ratio from 0.12462 to 0.17426. The outperformance of long-only sector rotation strategies confirms the findings of Sorensen and Burke (1986) and Stangl, Jacobsen and Visaltanachoti (2009) who state that sector rotation strategy that accounts for different stages of the business cycles outperforms the market.

Figure 2: Cumulative return of sector rotation strategies versus benchmark S&P500

This figure displays the cumulative return of sector rotation based on FF5 alpha. The returns are compared with the buy-and-hold cumulative return of S&P 500.



Overall, we conclude in this section that sector rotation is profitable, but that while the FF5 model is statistically superior, it does not lead investors to different, more profitable trading than the FF3 model. Having said this, note that the trading illustrated in this section is hypothetical, not applicable due to un-investable nature of Fama-French portfolios. The next

[12] Cumulative returns of strategies based on FF3 model are nearly identical.

section would provide a more realistic insight into the profitability of sector rotation based on FF5 vs. FF3 alphas, by using Sector Select SPDR ETFs.

3.4. Sector rotation with ETFs

Fama-French sectors portfolios are not readily investable and hence our strategies would be more valuable from practitioners' point of view if tested with sector ETFs. To this end, we use six 'Select Sector SPDR ETFs' as described in Section 2 to replicate our sector rotation strategies.

Table 9 reports the mean return, standard deviation and the Sharpe ratios of the strategies. We also report the maximum transaction costs that investor can afford to pay per each trade so that the Sharpe ratio of the given strategy breaks-even with the Sharpe ratio of the buy-and-hold. The table reports trading results based on FF5 and FF3 alphas for comparison. While strategies based on FF5 model have marginally higher standard deviation, they have higher mean returns and Sharpe ratios, and by and large allow for greater costs per trade. This clearly shows that FF5 model has the edge over its alternative when it comes to real-world trading with Sector Select ETFs. Hence, the analysis that follows will be focusing on the results based on FF5 model.

Reverting the comparison of results in Table 9 to those in Table 8, it can be seen that ETFs trading provides lower return than trading with Fama-French sector portfolios. This could be due to different trading periods. The ETF trading period is from January 1999 to December 2014, consisting of 192 months (26 recessionary months and 166 expansionary months) compared to the 576 trading months (83 recessionary months and 493 expansionary months) of Fama-French portfolios. Note that, the S&P 500 returns for those 192 trading months is 2.05% compared to the 5.67% rotation for the 576 trading periods. In Table 9, the Sharpe ratio of our long-only rotation strategy with FF5 is four times that of the buy-and-hold while the Sharpe ratio of the long-only strategy with accounts for recession is nearly 10 times that of the buy and hold, making it the most successful of our three rotation strategies. The long-short strategy remains unsuccessful. This can infer some conclusions about portfolio persistence: positive alphas utilised in the long-only strategies are more likely to lead to future positive alphas, while negative alphas are not a good predictor of future negative alphas leading to poor performance of long-short strategies that utilize them.

Break-even level of transaction costs per trade for each portfolio is calculated to assess the feasibility of our strategy for investors. Break-even transaction cost is expressed in basis points and it is the maximum cost per trade that can be paid, which equalises the Sharpe ratio of our rotation strategy to that of the buy and hold benchmark. The higher the break-even transaction costs are, the more feasible our strategy is. Similar to our rotation strategies with Fama-French sector portfolios, we find that long-only strategies provide higher return than S&P 500 benchmark whereas the long-short strategies provide lower return. The highest return is observed in the rotation strategy that takes long position in the corresponding sector ETFs during expansion period but invests in T-bill in recession period, more than 7% higher return than the benchmark. Break-even transaction cost of the rotation strategy (based on FF5 model) that invests in T-bills during recession suggests that investors can pay anything up to 326bps per trade and still generate Sharpe ratios higher than the buy-and-hold of the S&P 500. The breakeven costs per trade for long-only sector rotation with FF5 alphas are lower (148 bps per trade) but given that ETF trading has relatively low transaction costs (estimated 25bps, as per Section 2.2.3), the strategy is highly feasible for investors.

Table 9: Trading with Sector ETFs

This table reports the sector ETFs' annualised mean return, Standard Deviation, Sharpe Ratio and Break-even Transaction cost per trade of several strategies, as per Section 2.2.2. of the paper, over the trading period January 1999 to December 2014 (192 trading months: 166 expansionary periods and 26 recessionary periods). The buy-and-hold strategy represents the investment in the S&P 500 index. We use NBER recession index to determine recession and expansion period. Mean returns and standard deviations (Std. Dev.) have been annualised. The table reports trading results based on FF5 and FF3 alphas for comparison.

Trading Strategy	Mean Return	Std. Dev	Sharpe Ratio	Break-even TC
Long Only based on FF5 alpha	5.53%	16.29%	0.083911	147.73 BPS
Long Only based on FF3 alpha	3.7918%	14.9667%	0.055138	114.48 BPS
Long –Short based on FF5 alpha	0.52%	7.26%	-0.048748	Negative
Long –Short based on FF3 alpha	-0.0952%	6.6755%	-0.080490	Negative
Long Only with risk-free asset in Recession (FF5)	9.19%	13.75%	0.162814	326.66 BPS
Long Only with risk-free asset in Recession (FF3)	7.6744%	12.0048%	0.146824	398.27 BPS
Buy & Hold S&P 500	2.05%	16.88%	0.025382	N/A

This section documents that using FF5 model alphas for simple sector rotation with sector ETFs, as illustrated in this section, can lead to superior Sharpe ratios at an affordable level of trading cost, which is in line with what the statistical fit of the FF5 model to sector portfolios suggests.

4. Conclusions

This paper contributes to the literature on US sector performance, where we measure performance by a new Fama-French (2015) five-factor model. It further contributes to the scarce literature on sector rotation strategies by studying alpha-based sector rotation for the ten US Fama-French sector portfolios. We perform sector rotation based on the rolling alphas and assess whether five-factor model produces ‘true’ alphas that can be exploited by investors. With investors in mind, we also apply our sector rotation strategies using highly liquid S&P Select Sector SPDR ETFs that, in terms of definition and coverage, are a close match to Fama-French sectors.

When comparing three- and five-factor models, the OLS estimates suggest that FF5 explains the variability of the sector portfolio returns better than FF3, generating higher adjusted R-squared. The inclusion of the two additional factors (RMW and CMA) increases the statistical significance and decreases the alpha estimate in most sectors. Likelihood Ratio test for redundant variable confirms the significance of profitability (RMW) and investment (CMA) betas. Moreover, FF3 and FF5 exhibits structural change due to business cycles, suggesting that business cycles can be incorporated for more accurate trading strategies.

Our long-only sector rotation strategy based on FF5 rolling alphas of Fama-French US sector portfolios in the period January 1967 – December 2014 generates 5.40% higher return than the buy-and-hold of the S&P 500 index and nearly four times higher Sharpe ratio. The outperformance increases when we take business cycles into consideration. However, we observe that the long-short strategy is not successful relative to buy-and-hold. Trading with S&P Select Sector SPDR ETFs that match Fama-French portfolios in terms of definition, and are a feasible investment option for all investors confirms these findings at an acceptable level of transaction costs. Our findings are consistent to those of Sorensen and Burke (1986) and Stangl, Jacobsen and Visaltanachoti (2009).

Given that non-normal characteristics of sector returns are reported in this study, future research could involve the use of non-linear models. In addition, it would be of interest to extend our rotation strategies to different asset classes using five-factor Fama-French model.

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Appendix

Table A1: Summary of Sector rotation strategies used in the literature

The table provides the summary of the sector rotation studies, their study periods, the market, the details of the rotation strategy and the main findings.

Authors	**Country**	**Study Period**	**Rotations Strategies**	**Findings**
Sorensen and Burke (1986)	US	1972-1982	Relative strength index is measured, each month, for each industry based on the ratio of the group's current price to its average price over the prior six months. Top 3, 5, 7 and 10 of industry groups are then formed with the long position of highest rankings. Short position is taken if the group's rank fell below 30, 50 or 90 percentile.	Buying and holding best performing industry groups enhances portfolio returns.
Grauer, Hakansson and Shen (1990)	US	1934-1986	Multi-period portfolio theory is used to construct and rebalance portfolios that are composed from 12 industry indices. Investor forms value and equally weighted portfolios on the basis of utility function of corresponding index returns. Borrowing and lending is allowed, meaning that, if more (less) than 100% of asset is signalled to invest, investor borrow (lend) the remaining amount at a risk free rate.	Equally-weighted portfolios perform better than value-weighted portfolios. Portfolio that invest 200% of asset in the equally weighted indices by borrowing 100% at risk-free provides highest return in both sub-periods (1934-1986 and 1966-1986).
Sassetti and Tani (2006)	US	1998-2003	Rotating funds between 41 funds of the Fidelity Select Sector family based on the Rate of Change, Alpha, and Relative Strength Indicator calculated for the previous 30, 60 and 90 days.	Sector rotation strategy continuously outperforms buy-and-hold strategy. More specifically, rotation based on the alphas appears more stable than the one using the Rate of Change. However, sector rotation strategies outperform a benchmark only in the medium to long term.

Conover et al. (2008)	US	1973-2005	Rotation is based on changes in current and forecasted market conditions, portfolio weights are re-allocated across cyclical and noncyclical (defensive) sectors as the market conditions change.	Using monetary conditions as a rebalancing indicator provides higher excess return than the benchmarks.
Chong and Philips (2015)	US	2002-2014	Optimal portfolios of Select Sector SPDR ETFs are formed based on mean-variance and low-volatility optimisation. Portfolios are revisited every 6 months.	Mean-variance optimisation provides higher return than low-volatility optimisation. All rotation strategies exhibit loss in the recent recession period.
Shynkevich (2013)	US	1991-2001	A standard filter rule indicates a buy (sell) signal when price increases (decreases) by a fixed percentage from a subsequent low (high). 13000 trading rules are generated from this Filter; the rules include moving average, support and resistance, and channel breakout trading strategies.	Trading strategies are more successful when applied to sectors rather than to the aggregate market portfolio.
Dou et al. (2014)	US	1995-2010	Dynamic and static regime switching models are used to derive the expected returns and covariance matrix of sectors returns and switch between sectors is regime-dependent. Short-sell constraint and benchmark constraint are imposed to keep asset allocations close to market capitalisation weights in the MSCI world index.	The regime-dependent sector allocation is advantageous to exploit the defensive nature of some sectors. Dynamic regime switching model with no-constraint generate highest return among the other allocation strategies.
Beller, Kling and Levinson (1998)	US	1981-1995	Optimal sector portfolios are constructed based on the mean-variance optimiser and the predictions of Bayesian multivariate regression model.	Portfolio with the highest predicted returns generates the highest mean returns. Portfolios that long the higher return industries and short the lower return industries have the second highest return.

Table A2: Industry Definition of Fama-French Sector Portfolios and Select Sector SPDR ETFs

The Table shows industry definitions and SIC codes of Fama-French sectors and six comparable Select Sector SPDR ETFs

Fama-French Industries			Select Sector SPDR ETFs	
Industry	**Industries**	**SIC Codes**	**SPDR**	**Industries**
Consumer Non Durables	Food, Tobacco, Textiles, Apparel, Leather, Toys	0100-0999 2000-2399 2700-2749 2770-2799 3100-3199 3940-3989	Consumer Staples	Food and drug retailing, Beverages, Food products, Tobacco, Household products, and Personal products
Consumer Durables	Cars, TV's, Furniture, Household Appliances	2500-2519 2590-2599 3630-3659 3710-3711 3714-3714 3716-3716 3750-3751 3792-3792 3900-3939 3990-3999	Consumer Discretionary	Automobiles and components, Consumer durables, Apparel, Hotels, Restaurants, Leisure, Media, and Retailing
Energy	Oil, Gas, and Coal Extraction and Products	1200-1399 2900-2999	Energy	Crude oil and Natural gas
HiTech	Business Equipment-Computers, Software, and Electronic Equipment	3570-3579 3622-3622 (Industrial controls) 3660-3692 3694-3699 3810-3839 7370-7372 (Services - computer programming and data processing) 7373-7373 (Computer integrated systems design) 7374-7374 (Services - computer processing, data preparation) 7375-7375 (Services - information retrieval services) 7376-7376 (Services - computer facilities management service) 7377-7377 (Services - computer rental and leasing) 7378-7378 (Services - computer maintenance and repair) 7379-7379 (Services - computer related services) 7391-7391 (Services - R&D labs) 8730-8734 (Services - research, development, testing labs)	Technology	Internet software and service companies, IT consulting services, Semiconductor equipment and products, Computers and peripherals, Diversified telecommunication services and wireless telecommunication services
Health	Healthcare, Medical Equipment, and Drugs	2830-2839 3693-3693 3840-3859 8000-8099	Health Care	health care equipment and supplies, health care providers and services, biotechnology, and pharmaceuticals industries
Utilities	Utilities	4900-4949	Utilities	companies that produce, generate, transmit or distribute electricity or natural gas