Does History Repeat Itself? Business Cycle and Industry Returns

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We document that industries with a higher historical Sharpe Ratio have higher expected returns conditional on the business cycle. A long-short sector rotation strategy generates annualized alpha of 11.91% (14.02%) in Fama-French three-factor (five-factor) model from 1985 to 2014. Our sector rotation strategy alpha is not due to industry momentum or other related anomalies and is less likely to be driven by a risk-based explanation. Firms in our long portfolio have better fundamentals, more upward revisions of analyst forecasts, and more positive analyst forecast errors. Our results suggest that investors do not fully incorporate business cycle variation in cash flow growth and highlight the importance of business cycle on the cross-sectional return dispersion of industry portfolios.

Keywords: Business Cycle, Industry Returns, Sector Rotation Strategy, Cash Flow Growth

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I. Introduction

What explains the cross-sectional dispersion of industry returns? Despite the success of various factor models in explaining the cross-section of returns, Fama and French (1997) and Lewellen, Nagel, and Shanken (2010) demonstrate the failure of many leading asset pricing models when industry portfolios are used as test assets. Given the business cycle frequency variation of industry performance, economic intuition would suggest macroeconomic conditions might be important in understanding the cross-industry difference in returns. However, direct tests of industry portfolio returns on business cycle variables are less likely to be effective, as macroeconomic quantities (such as consumption growth) have shown to have poor explanatory power of expected returns even for the aggregate market portfolio.

We take a slightly different approach to understand the impact of the macroeconomy on the cross-sectional return dispersion of industry portfolios. We hypothesize that past performance of a particular industry is informative for predicting future returns of the same industry. Moreover, due to the heterogeneous sensitivity of different industries to economic conditions (Gomes, Kogan, and Yogo (2009)), time variation of expected returns should be different across industries. Conditional on business cycle variation, industry portfolios with better historical performance tend to outperform other industries in the future. Therefore, we examine time-varying expected returns in the cross-section of industries using a regime-dependent historical industry Sharpe Ratio.

We document three main findings in this paper. First, conditional on the business cycle, industry portfolios with a higher historical Sharpe Ratio tend to have higher expected returns. One standard deviation increase in conditional Sharpe Ratio leads to 2.34% increase in annualized expected returns when the economy is bad, and 1.67% increase when the economy is good. Second, a sector rotation strategy based on this finding generates annualized excess return of 8.45%, with an annualized alpha of 11.91% (14.02%) in Fama-French three-factor (five-factor) model from 1985 to 2014. The returns remain significant even after controlling for risk factors and other related anomalies. Third, we attempt to understand the sources of the sector rotation strategy profitability. We do not find direct evidence for a risk-based explanation, but it is still possible, as there may be some omitted measures of risk that we don't account for. Instead, our evidence suggests that the profitability of the strategy is more likely due to investors' inability to fully incorporate business cycle variation in expected cash flow growth.

The idea that industry performance is linked to the business cycle is not new as evidenced by the various "sector rotation" strategies widely employed by portfolio and mutual fund managers.[1] However, the plain-vanilla sector rotation strategy relies on the manager's ability to decipher current macroeconomic conditions, which is not an easy task given the backward-looking nature of NBER definition of recessions. In contrast, to measure business cycle, we construct a production-based macroeconomic variable, output gap, as in Cooper and Preistley (2009). We define the regime for year y by the sign of output gap on November of year $y-1$, so two regimes are defined in our analysis. Given the regime of year y, we measure the past performance as the historical Sharpe Ratio in the same regime. If the regime is positive, the regime Sharpe Ratio captures the expected return adjusted for volatility when the output gap is positive. It is easy to construct and feasible. We show that industry portfolios with higher regime Sharpe Ratio tend to have higher returns. Our results remain similar when we control for relevant characteristics including average firm size, book-to-market ratio, and past one year return, or control for factor loadings on Fama-French three-factor model.

We examine the economic significance of our finding by constructing the following sector rotation strategy. By the end of year $y-1$, we define the regime for year y and calculate the corresponding regime Sharpe Ratio for each industry portfolio. We sort industry portfolios based on the regime Sharpe Ratio, then long the industries in the highest decile and short industries in the lowest decile. From 1985 to 2014, the equal-weighted long-short sector rotation strategy has an excess return of 8.45% per year. The abnormal returns range from 8.86% to 14.46% in conventional factor models. It is robust to using value-weighted strategy, using conditional factor models, using 30 value-weighted industry portfolios, and excluding

[1]As of November 3, 2015, SPDR provides 11 sector EFTs with total net asset value of $63.08 billion, and 19 industry ETFs with total net asset value of $10.81 billion. (Source: https://www.spdrs.com/). Fidelity also provides more than 250 sector ETFs (Source: https://www.fidelity.com/etfs/sector-etfs).

the period after the start of the recent financial crisis.

Next, to ensure that our strategy cannot be explained by existing anomalies which rely on past return information, we consider industry momentum (Moskowitz and Grinblatt (1999)), sector rotation strategy based on cross-industry predictability (Rapach, Strauss, Tu, and Zhou (2015)), time-series momentum (Moskowitz, Ooi, and Pedersen (2012)), and long-term reversal (De Bondt and Thaler (1985)). We regress the strategy return on CAPM or Fama-French three-factor model augmented by one of those anomalies. For the equal-weighted strategy, the annualized abnormal returns in two-factor regression range from 6.98% to 9.92%. The abnormal returns are higher in four-factor regression. These results indicate that our strategy is not explained by these existing anomalies.

We further test whether output gap is a better proxy for business cycle than financial variables. We employ ten financial variables which are used in Goyal and Welch (2008) to define business cycle and conduct sector rotation strategy. The strategy based on Net Equity Expansion (NTIS) is the only one which generates positive significant excess returns for both equal-weighted and value-weighted strategy, but the statistical and economic significance is much lower than that of our main strategy. We also use simulation to generate regime series, which has the same number of positive/negative regimes as that defined by output gap. We find that 1,000 simulations are required to obtain one regime series to beat our original strategy, thus mitigating data mining concerns.

After showing the robustness of our strategy, we proceed to test potential explanations to the profitability of our strategy. The first explanation is risk-based. It is possible that the long portfolio may be riskier than the short portfolio, thus requiring higher risk compensation. We first check whether our long and short portfolios are different across multiple risk measures, such as, market beta, volatility, skewness, and kurtosis. We do not find any significant difference between our long and short portfolios on these dimensions. Moreover, if the long portfolio is riskier than the short portfolio, the strategy return should capture some risk information. So, we treat our trading strategy return as a risk factor and augment it by the market factor. We apply standard Fama-Macbeth two-stage approach to 49 value-weighted industry portfolios. We do not find evidence that the factor is priced. Both these results suggest that our sector rotation strategy return is not likely to be a compensation for risk.

An alternative explanation for the profitability of the sector rotation strategy that we document is related to cash flow growth. It is possible that investors may not fully incorporate business cycle variation in the cash flows of the industries in our long and short portfolios. Specifically, investors may underestimate future cash flow growth for firms in the long portfolio and overestimate future cash flow growth for firms in the short portfolio. Their revisions on expected cash flow growth according to cash flow news can drive the price movements and generate the return difference. We test for this cash flow-based explanation. We proxy cash flow growth by sales growth as in Gomes, Kogan, and Yogo (2009). Our firm-level panel regression shows that firms in the long portfolio have 2.50% higher sales growth than firms in the short portfolio. We further check the operating performance measured by profitability and Tobin's Q, which are also higher for firms in the long portfolios. Both these results confirm that firms in the long portfolio have better fundamentals.

In an efficient market, if the cash flow growth that we document is expected, then there should be no additional market reaction to the realization of these fundamentals. We further test whether cash flow growth is unexpected. As we cannot directly measure investors' expectations, we use analyst forecasts as a proxy for investors' forecasts as argued in So (2013). Change in consensus analyst forecasts is used as a proxy for revisions in expected future cash flow growth. We also construct analyst forecast errors to measure unexpected cash flow news. We find that firms in the long portfolio have more upward revisions in the consensus analyst forecasts and more positive analyst forecast errors. In line with these positive analyst forecast errors, these firms also have higher cumulative returns around earnings announcements days. Overall, the combined evidence supports that the cash flow growth is unexpected. It appears that the profitability of sector rotation strategy that we document in this paper, is more likely driven by the inability of investors to fully incorporate the business cycle variation in the cash flows of these industry portfolios.

There is a large practitioner literature on sector rotation strategies. One popular strategy is based on the well-defined economic cycle using NBER indicators recession (Stovall (1996)).[2] Since the NBER indicator is backward-looking, it is very hard to identify the change of the stage accurately. Implementing the strategy in real time seems implausible. Moreover, although it has been widely discussed among practitioners for two decades, there is little empirical evidence supporting the superior performance of the strategy. On the contrary, Jocobsen, Stangl, and Visaltanachoti (2009) show that a conventional strategy that perfectly times the business cycle can at best beat the market by 2.3% from 1948 to 2007. This out-performance disappears after controlling for transaction costs.

The sector rotation strategy that we propose in this paper is different from the conventional practitioner strategy in several aspects. First, the strategy relies on output gap calculated from real-time industrial production to define two regimes. It is easy to construct and feasible. Second, industries in our strategy are time-varying. We adjust our strategy according to new information instead of specifying which industries to hold at a certain stage of the business cycle. Third, in addition to buying industries which are expected to perform well, we short industries which are expected to have bad performance. Both sides of the long-short strategy contribute to significant risk-adjusted returns. Finally, we try to examine systematically why sector rotation strategy is profitable. Our strategy is also different from a recent sector rotation strategy proposed by Rapach, Strauss, Tu, and Zhou (2015) because their strategy relies on slow diffusion of information across interdependent industries instead of business cycle. Also, our strategy has much lower re-balancing frequency, leading to lower transaction costs. In Section III.C, we show that our strategy cannot be explained by their strategy.

Our paper is closely related to Chordia and Shivakumar (2002) and Avramov and Chordia (2006) that consider business cycle predictors. Chordia and Shivakumar (2002) argue that time-varying expected returns may explain momentum strategy by showing momentum profits are related to macro variables. Avramov and Chordia (2006) demonstrate that business cycle

[2] Stovall (1996) defines a five-stage business cycle according to the NBER recession indicator, including early expansion, middle expansion, late expansion, early recession, and late recession. In each stage, some industries are expected to outperform other industries. For example, at the early stage of the recession, utilities and telecoms industries are recommended. At the late stage of the recession, he suggests consumer cyclical and financial industries.

predictors are beneficial for optimizing a portfolio of individual stocks and cash. In particular, Avramov and Chordia (2006) investment strategies change their investment styles over the business cycle. Over recessions they load less heavily on momentum stocks and more heavily on small-cap stocks. Similarly, we show that switching investment across industry portfolios over the business cycle is profitable. We extend this literature by examining the different time-varying patterns across industry portfolios and showing that these patterns are persistent.

Our sector rotation strategy is related to trading strategies based on calendar or geographical location that are documented in the literature. A trading strategy based on geographical location takes advantage of the differential performance of stocks from different states/countries due to the difference of the local economy. Korniotis and Kumar (2013) use state-level macro variables as predictors and construct a profitable sector rotation strategy of state-level portfolios. Beber, Brandt, and Luisi (2014) show the profitability of a country-level sect rotation strategy. Keloharju, Linnainmaa, and Nyberg (2015) document the profitability of a calendar strategy where in, past winning stocks in a given month tend to outperform other stocks in the corresponding future month. The profitability of this calendar strategy extends to anomalies, commodities, international markets, and even at the daily frequency.

Our paper is related to the literature of time-varying expected returns. Fama and French (1989) argue that expected returns are higher when the economic conditions are bad. Lustig and Verdelhan (2012) show that expected returns, adjusted for volatility, are higher during recessions. Goyal and Welch (2008), Campbell and Thompson (2008) compare the power of numerous state variables, most of which are financial variables, to predict market returns. Cooper and Preistley (2009) show that output gap, a production-based macro variable, strongly predicts market returns.

Our paper also contributes to the literature explaining the cross-section of industry returns. Fama and French (1997) and Lewellen, Nagel, and Shanken (2010) show that asset pricing models do not explain the cross-section of industry returns well. Gomes, Kogan, and Yogo (2009) show that industries producing durable goods have higher average returns because their demands are more cyclical and riskier. Croce, Marchuk, and Schlag (2016) document that firms in the leading industries have higher average returns than that of firms in the lagging industries. Moskowitz and Grinblatt (1999) find that winning industries over the past 6 to 12 months outperform losing industries. Addoum and Kumar (2016) show that changes in political climate can be used to predict industry returns. We add to this literature by showing that, conditional on the business cycle, industries performing well in the past tend to outperform other industries in the future.

Finally, our paper is related to the literature that investors fail to incorporate all available information in making forecasts. Bernard and Thomas (1990) show that investors do not fully incorporate information of current earnings when forecasting future earnings. Chang, Hartzmark, Solomon, and Soltes (2016) document that investors fail to consider seasonal patterns in earnings fully. We find that investors do not price information regarding business cycle variation in cash flow growth.

The rest of the paper proceeds as follows. We describe the data in Section II. Section III presents the main empirical results. Section IV tests alternative explanations to the profitability of sector rotation strategy. We conclude the paper in Section V.

II. Data

Our sample period is from 1927 to 2014. We start the sample from 1927 because it is the first year to have full-year data in Kenneth French's industry portfolios. Our first task is to find a good proxy for the business cycle. Given our purpose, this proxy should be very sensitive to the change of business cycle and related to stock returns. From this perspective, output gap, a production-based macro variable, stands out. Brave (2009) documents that compared with consumption, production is more sensitive to the business cycle. Also, Cooper and Priestley (2009) show that output gap strongly predicts market returns. We construct output gap as in Cooper and Priestley (2009),

$$ip_t = \alpha + \beta_1 * t + \beta_2 * t^2 + \epsilon_t, \tag{1}$$

where ip_t is the logarithm of monthly industry production obtained from FRED, and t is a time trend. The standardized residual ϵ_t is used as output gap. The time-series of the output gap is plotted in Figure 1. It appears that output gap drops significantly around recessions. For example, the output gap is 0.58 by the end of 2007 and starts to drop dramatically since the beginning of 2008. It hits the lowest value on June 2009, which is -0.96. Interestingly, NBER classifies the period from January 2008 to June 2009 as a recession.

We define the business cycle for year y according to the sign of output gap on November of year $y - 1$. We intentionally leave one month gap because the November data is the latest output gap we know by the end of year $y - 1$. Each year is defined as either positive regime or negative regime. Negative regime indicates that the current industrial production is below the quadratic trend, implying the current state of the economy is bad. There are 45 negative-regime years and 42 positive-regime years from 1928 to 2014. The average of annualized market excess returns is 4.55% for positive-regime years and 11.22% for negative-regime years. It is consistent with Fama and French (1989), Cooper and Priestley (2009), and Lustig and Verdelhan (2012) that expected return is higher when the economy is bad.

To avoid look-ahead bias, we use vintage data instead of full sample time-series to construct output gap in our empirical analysis. Specifically, by the end of year $y - 1$, we run the time-series regression with all available data starting from 1927 to November of year $y - 1$. The standardize residual is used to define regimes. This approach guarantees that our sector rotation strategy is feasible.

We obtain 49 value-weighted industry portfolios from Kenneth French's data library. It has the largest number of industries in all Fama-French industry classifications. A finer industry classification ensures that firms within the same industry have similar price movements. Following Hong, Torous, and Valkanov (2007), nine industry portfolios without full time-series data from 1927 to 2014 are excluded from our analysis. As shown in Figure A1, 40 industry portfolios in our sample cover at least 86.49% of the total market capitalization and 83.33% of the total number of firms. Both averages are about 95%, which alleviates the concern about sample selection.

Summary statistics for annualized excess returns of industry portfolios from 1927 to 2014 are reported in Table I. In the full sample, Tobacco Product (Smoke) has the highest Sharpe Ratio, 0.49, while Real Estate (RlEst) has the lowest Sharpe Ratio, 0.21. The cross-sectional standard deviation of Sharpe Ratio is 0.07. Comparing the performance of industry portfolios across regimes, all industry portfolios except Printing and Publishing (Books), Construction (Cnstr), Coal, and Real Estate (RlEst) have higher Sharpe Ratio in negative regimes. It is consistent with the idea that most industry portfolios have time-varying expected returns adjusted for volatility, which are higher in the bad time.

In negative regime, Food performs the best with Sharpe Ratio of 0.71. Coal is the worst with Sharpe Ratio of 0.11. The cross-sectional standard deviation of Sharpe Ratio is 0.14. In contrast, Coal has the highest Sharpe Ratio in positive regime, 0.44. The Sharpe Ratio of other industry is almost 0. The cross-sectional standard deviation of Sharpe Ratio is slightly lower, 0.10. Both dispersions in Sharpe Ratio are higher than that of the full sample, implicitly providing us the opportunity to construct long-short strategy conditioning on regimes. A greater dispersion helps us differentiate industries.

Our main analysis is conducted using the most recent 30-year data from 1985 to 2014 because we need a long enough time series to estimate the historical performance of industry portfolios conditional on regimes. Also, it would be more appropriate to conduct sector rotation strategy in a period with high liquidity and low transaction costs. Since we use industry portfolios to construct the strategy, we report the number of firms in each industry portfolio from 1985 to 2014 in Table II. Most of the industry portfolios, on average, have more than 30 stocks. However, it raises concerns about whether some portfolios are well-diversified as some portfolios have less than ten stocks at some time periods. To avoid idiosyncratic risk, when we form the strategy by the end of year $y-1$, we only consider industry portfolios with more than 30 stocks at that time.[3]

[3]Elton and Gruber (1977) document that adding stocks to a portfolio of 15 stocks still reduces the risk significantly. Statman (1987) shows that at least 30 stocks are needed for constructing a well-diversified portfolio. Campbell, Lettau, Malkiel, and Xu (2001) argue that as idiosyncratic volatility increases over time, the number of stocks required to construct a given level of well-diversified portfolio goes up.

To explain why sector rotation strategy is profitable, we merge CRSP, COMPUSTAT, and I/B/E/S data. To be consistent with the construction of industry portfolios, we include common stocks (share code: 10 or 11) traded on NYSE, NASDAQ, and AMEX (exchange code: 1 or 2 or 3) in the firm-level analysis. We match firms to one of the 49 industries according to Fama-French industry classifications. Firms are dropped if they cannot be assigned to any of the industries. The merged dataset is used to construct sale growth, profitability, Tobin's Q, change in monthly consensus analyst forecasts, analyst forecast errors, and cumulative returns around earnings announcements. To avoid extreme observations, we winsorize firm fundamental measures and analyst forecast errors at 1% level. Summary statistics for those measures are reported in Table A3.

III. Empirical Results

We first empirically show that conditional on the business cycle, industries with better past performance tend to outperform in the future. Then, we conduct sector rotation strategy according to this finding. Given the regime, at the beginning of the year, we long (short) industry portfolios which are expected to perform well (badly) based on the historical regime Sharpe Ratio. We show that our sector rotation strategy remains profitable after controlling for conventional risk factors and cannot be explained by existing related anomalies. In the last part of this section, we show that output gap is a better proxy for business cycle compared with financial variables and address a concern about data mining through simulation.

A. Regime Sharpe Ratio and Excess Return

To measure the past performance conditional on regime, we introduce regime Sharpe Ratio ($Regime\_SR$). It is the Sharpe Ratio computed from past years in a given regime. Given the regime of year y, we collect all historical data from 1928 to year $y-1$ for industry i, and the regime Sharpe Ratio for industry i, $Regime\_SR_{i,y-1}$, is calculated as follows,

$$Regime\_SR_{i,y-1} = \frac{\mu_{i,y-1}}{\sqrt{(\sum_{y'=1928}^{y-1}(R_{i,y'} - \mu_{i,y-1})^2 * I_{(y',y)})/(\sum_{y'=1928}^{y-1} I_{(y',y)})}},$$
$$\mu_{i,y-1} = (\sum_{y'=1928}^{y-1} R_{i,y'} * I_{(y',y)})/(\sum_{y'=1928}^{y-1} I_{(y',y)}). \tag{2}$$

where y' is a year from 1928 to $y-1$, $R_{i,y'}$ is the excess return of industry i in year y', and $I_{y',y}$ is set to 1 if year y' has the same regime as year y. The numerator is the mean excess return and the denominator is the standard deviation of excess return in the given regime. We use Sharpe Ratio instead of simple average return because it controls for the level of volatility.

To demonstrate the persistence in performance conditional on the regime, we run a panel regression from 1985 to 2014.

$$Ret_{i,y} = \alpha + \beta * Regime\_SR_{i,y-1} + \gamma_y * X_{i,y-1} + I_y + \epsilon_{i,y}. \tag{3}$$

The dependent variable is the annual excess return of industry portfolio i in year y. The main independent variable is regime Sharpe Ratio, $Regime\_SR_{i,y-1}$. We include year fixed effect to control for unobserved common shocks. $X_{i,y-1}$ are control variables which have been shown to predict returns including industry characteristics and risk factor loadings. Standard errors are clustered by year and industry. The results are reported in Table III Panel A.

The coefficient of interest is β. A significant positive β reflects the persistent performance of industry portfolios conditional on the regime. To reduce possible noise from industry portfolios with a small number of stocks, from Column (1) to Column (5), we require an industry portfolio to have more than 30 stocks by the end of year $y-1$ to be included. We include all 40 industry portfolios from Column (6) to Column (10).

In Column (1), we run univariate regression with $Regime\_SR$. The coefficient is 0.167 (t-stat: 2.52). The result indicates that, when the output gap is negative, one standard deviation increase in $Regime\_SR$ leads to 2.34% increase in annualized expected return. It is associated with 1.67% increase when the output gap is positive.[4] It supports our hypothesis that conditional on the regime, industries with a higher historical Sharpe Ratio have higher expected returns.

One possible concern about the result in Column (1) is that industries with higher $Regime\_SR$ are those with higher unconditional historical Sharpe Ratio. To rule out this possibility, we only include the historical Sharpe Ratio, $Historical\_SR$, in Column (2). It is calculated using all available historical data. Although the coefficient is positive (0.135), but it is not statistically significant (t-stat: 1.14). It suggests that conditional Sharpe Ratio provides more relevant information for predicting future industry returns than unconditional Sharpe Ratio.

To further support that the predictive power is closely tied to the regime, we run a univariate regression on Sharpe Ratio computed from historical data from the opposite regime (Opp_Regime_SR). Specifically, if the regime for year y is positive, Opp_Regime_SR is the Sharpe Ratio calculated using data in negative regime years. As shown in Column (3), the coefficient is -0.090 (t-stat: -1.64). It highlights the importance of accurately identifying the regime because information from the opposite regime is negative.

In Column(4), we control for industry characteristic which has been shown to predict returns: the logarithm of average market capitalization ($Log(Size)$), industry aggregate book-to-market ratio (BM), and 11-month cumulative return from one year ago to one month ago (Ret_212)[5]. It appears that industries with more small firms, value firms, and firms with higher past one-year return tend to have higher returns. The result is consistent with size effect, value effect, and momentum effect. However, all effects are insignificant in this setting. On the contrary, the coefficient for $Regime\_SR$ is 0.182 (t-stat: 3.02).

We control for risk factor loadings in Column (5). We include factor loadings on Fama-French three factors: market factor (β_{MKT}), SMB factor (β_{SMB}), and HML factor (β_{HML}),

[4]When output gap is negative, the cross-sectional standard deviation of Sharpe Ratio is 0.14. Given that the coefficient is 0.167, the increase in annualized expected return associated with one standard devision increase in $Regime\_SR$ is 0.167*0.14=2.34%. Since the cross-sectional standard deviation of Sharpe Ratio is 0.10 when output gap is positive, similarly, the increase in expected return would be 0.167*0.10=1.67%.

[5]In an unreported analysis, we alternatively control for 5-month cumulative return from six months ago to one month ago. The result remains similar.

which are estimated using 60-month rolling window till the end of year $y-1$. Our result remains significant. The coefficient for *Regime_SR* is 0.174 (t-stat: 3.00). We repeat the analysis with all 40 industry portfolios from Column (6) to Column (10) to mitigate the concern about sample selection. Both economic and statistical significance remains.

Admittedly, the momentum effect controlled in Column (4) is not the same as that discovered in Jegadeesh and Titman (1993), and Moskowitz and Grinblatt (1999), since the dependent variable is annual excess return but the momentum strategy is rebalanced monthly. To further rule out the possibility that our finding is driven by industry momentum effect, we redo the analysis at the monthly frequency. Specifically, the dependent variable becomes monthly industry excess return. *Regime_SR* is calculated from past monthly returns from months which have the same regime as current month. The results are reported in Table III Panel B. In Column (1), the coefficient for *Regime_SR* is 0.037 (t-stat: 2.28), consistent with our result at the annual frequency. In univariate regression, both *Historical_SR* and *Opp_Regime_SR* are insignificant. We are particularly interested in the result in Column (4) where we control for industry characteristics including past one-year return. The coefficient for *Ret*_212 is 0.013 (t-stat: 1.74), suggesting there does exist industry momentum effect in our data. However, the coefficient for *Regime_SR* is 0.030 (t-stat: 2.56). The result differentiates our finding from industry momentum effect.

One concern about our result is that the dependent variable does not control for the level of volatility, while the main independent variable controls for it. To address the concern, we replace excess return by Sharpe Ratio calculated from monthly returns. The results are similar. The results remain unaffected if we use Fama-MacBeth regression instead of panel regression with time fixed effect.

B. Sector Rotation Strategy

To examine the economic significance of our finding, we conduct sector rotation strategy from 1985 to 2014. Specifically, by the end of year $y-1$, we sort industry portfolios according to the regime Sharpe Ratio given the regime of year y. We long industry portfolios in the highest decile and short industry portfolios in the lowest decile. Within the decile, we create both equal-weighted and value-weighted portfolios.

For our main result, similar to the regression analysis in Section III.A, we only include well-diversified industry portfolios. Specifically, only industry portfolios with more than 30 stocks at the time of construction are considered. As shown in Figure A2, on average, we have 423 stocks in the long portfolio and 230 stocks in the short portfolio. Hence, the portfolio performance should not be driven by the extreme performance of a few stocks.

The components of the long and short portfolios are reported in Table A1. When output gap is negative, the strategy is most likely to long Food, Drugs, Retail, and Household industries, and short Construction, Steel, Business Service, and Real Estate. When output gap is positive, Medical Equipment and Construction are preferred, but Autos and Other industry are shorted. Based on the portfolio components, we calculate the annual turnover, which is defined as the percentage of industry portfolios that are replaced. [6] Average annual turnover is 20% for the long portfolio and 22.2% for the short portfolio. The low turnover indicates that transaction cost should not be a concern for the implementation of our strategy.

Figure 2 plots the portfolio value of investing \$1 in the long, short, market, or risk-free portfolio at the end of 1984. The equal-weighted long portfolio has a value of \$68.7 by the end of 2014. The value of the value-weighted long portfolio is \$65.4. The performance of the equal-weighted long portfolio nearly triples the performance of the market portfolio, which is worth of \$24.6. Admittedly, the long portfolio has two big crashes around the dot-com bubble and the recent financial crisis. However, it's not surprising because the whole market crashes. The short portfolio seems to pick up stocks which do not perform well. It almost has the same performance as the risk-free asset before the interest rate hit the zero lower bound in 2008.

Table IV reports the performance of the short, long, and long-short portfolios. The annualized excess return is 8.45% (t-stat: 2.86) for the equal-weighted strategy and 7.68% (t-stat:

[6] The calculation is based on Table A1. Since the long portfolio holds the same industries in 1985 and 1986, the industry turnover is 0 in 1986. In 1995, all industries in the long portfolio have been replaced, therefore, the industry turnover is 1. Admittedly, the stock turnover should be higher than the industry turnover because the industry portfolios are rebalanced every year.

2.36) for the value-weighted strategy. To control for conventional risk factors, we regress the monthly excess return of the portfolio on risk factor models,

$$R_{p,t} = \alpha + \sum_{i=1}^{K} \beta_i f_{i,t} + \epsilon_t. \quad (4)$$

We consider CAPM, Fama-French three-factor model (Fama and French (1993)), Carhart four-factor model (Carhart (1997)), Fama-French three-factor model augmented by Durability factor (Gomes, Kogan, and Yogo (2009)),[7] Pastor-Stambaugh four-factor model (Pastor and Stambaugh (2003)), Hou-Xue-Zhang q-factor model (Hou, Xue, and Zhang (2015)), and Fama-French five-factor model (Fama and French (2015)). For the equal-weighted strategy, annualized abnormal returns range from 8.86% (t-stat: 2.78) to 14.46% (t-stat: 4.78). More interestingly, annualized abnormal returns for the short portfolio range from -5.00% (t-stat: -2.30) to -8.85% (t-stat: -4.44). In contrast, the long portfolio earns abnormal returns between 3.86% (t-stat: 2.37) and 5.61% (t-stat: 3.37). The abnormal returns of our strategy come from both the long side and short side, which is an advantage of our strategy compared with the long-only conventional sector rotation strategy (Stovall (1996)). The value-weighted strategy earns abnormal returns ranging from 7.58% (t-stat: 2.10) to 16.23% (t-stat: 4.92). The significant α indicates that our strategy cannot be explained by traditional factor models.

The corresponding factor loadings are reported in Table A2. Sector rotation strategy has negative factor loadings on all factors except momentum factor (MOM) and liquidity factor (LIQ). It is not surprising that sector rotation strategy has significant positive loading on MOM because regime Sharpe Ratio may contain the past one-year information if the current regime is the same as that of last year. Despite the significant loading, the abnormal return in Carhart four-factor model is 9.95% (t-stat: 3.94) for the equal-weighted strategy and 9.75% (t-stat: 3.39) for the value-weighted strategy. The loading on LIQ is insignificant.

Panel B reports the performance of sector rotation strategy according to unconditional historical Sharpe Ratio. The excess returns for both equal-weighted and value-weighted strat-

[7] Gomes, Kogan, and Yogo (2009) document that durable sector has higher average return than services sector because durable goods are more cyclical.

egy are negligible. The economic magnitudes are marginal, about 2.5%. We also construct sector rotation strategy according to the Sharpe Ratio computed from the opposite regime. As shown in Panel C, the excess returns is -4.72% (t-stat: -1.77) for the equal-weighted strategy and -5.81% (t-stat: -2.12) for the value-weighted strategy. The significance disappears after risk factors are controlled for. All results in Table IV indicate that conditional Sharpe Ratio provides important information for predicting industry returns.

Since our strategy is conditional on business cycle, it is possible that factor loadings change as macroeconomic conditions shift. To address the potential impacts of time-varying risk exposures, we modify equation (4) and allow regime-dependent factor loadings,

$$R_{p,t} = \alpha + \sum_{i=1}^{K} \beta_i^+ f_{i,t} * I_t^+ + \sum_{i=1}^{K} \beta_i^- f_{i,t} * I_t^- + \epsilon_t, \tag{5}$$

where I_t^+ is a dummy variable which is set to 1 if month t is in positive regime. Otherwise, I_t^- is equal to 1. As shown in Table V Panel A, abnormal returns slightly decrease. The abnormal return in Hou-Xue-Zhang q-factor model experiences the biggest decrease. It drops from 14.46% (t-stat: 4.78) to 11.63% (t-stat: 3.84) for the equal-weighted strategy, but both the economic and statistical significance remains.

We include all 40 industry portfolios without imposing filters on the number of stocks in Panel B. The results are slightly weaker compared with Table IV Panel A. abnormal returns range from 6.68% to 11.37% for the equal-weighted strategy, and from 7.49% to 15.42% for the value-weighted strategy. All p-value are less than 5%. The difference indicates that imposing some requirements on the number of stocks can reduce the impacts of idiosyncratic risks and lead to stronger results. To test our conjecture, we impose different filters on the number of stocks. As shown in Figure A3, as we increase the filter from 0 to 40, the performance of sector rotation strategy almost monotonically increases. It appears reasonable to impose the filter of requiring 30 stocks for industry portfolios. For the remaining of the paper, we keep this requirement.

To examine whether our results are limited to one kind of industry classifications, we use 30 value-weighted industry portfolios obtained from Kenneth French's Data Library to conduct sector rotation strategy. All industry portfolios have data since 1927. In Panel C, the risk-adjust returns of sector rotation strategy are significant. To check whether the bull market after the recent financial crisis drives our strategy, we exclude the holding period after 2007 when the monetary policy has a significant impact on the stock markets. As reported in Panel D, annualized abnormal returns range from 7.81% to 14.29% for the equal-weighted strategy, and from 7.39% to 17.86% for the value-weighted strategy. It indicates that our results are not driven by the recent period. In an unreported result, we conduct sector rotation strategy at the monthly frequency. The strategy is still profitable.

C. Related Anomalies

To rule out the possibility that our sector rotation strategy can be explained by well-known anomalies which rely on past return information, we examine four related anomalies in addition to momentum (Jegadeesh and Titman (1993)): industry momentum (Moskowitz and Grinblatt (1999)), sector rotation strategy based on cross-industry predictability (Rapach, Strauss, Tu, and Zhou (2015)), time-series momentum (Moskowitz, Ooi, and Pedersen (2012)), and long-term reversal (De Bondt and Thaler (1985)). We have already shown in Table III and Table IV that our strategy is robust after controlling for traditional momentum strategy.

Moskowitz and Grinblatt (1999) show that winning industries in the past six months are more likely to outperform past losing industries in the next six months. Rapach, Strauss, Tu, and Zhou (2015) demonstrate that industry returns can be strongly predicted by the lag returns of other industries due to slow diffusion of information. They form a long-short portfolio based on the predicted returns and rebalance it monthly. Moskowitz, Ooi, and Pedersen (2012) document that a security's past 12-month excess return positively predicts its future return. Time-series momentum strategy longs assets with positive excess returns over past 12 months and shorts assets with negative excess returns. De Bondt and Thaler (1985) find that losers over the past 36 months to 60 months tend to be the winners in the future. Conceptually, our strategy is different from these strategies because we rely on much longer historical information and the past information is conditional on the business cycle. In contrast, the existing anomalies rely on recent period.

Furthermore, we differentiate our strategy to related anomalies empirically. We replicate industry momentum factor (IM) and sector rotation strategy based on cross-industry predictability (CIP)[8] following their papers. The average annualized excess return is 10.36% (t-stat: 2.42) for IM and 8.65% (t-stat: 2.52) for CIP. We obtain time-series momentum factor (TSM) from Tobias Moskowitz's website and long-term reversal factor (LTR) from Kenneth French's Data Library. We run two regression specifications. The first regression includes market factor and one of the related anomalies. The second specification has Fama-French three factors and one of the related anomalies. If any of these anomalies can explain our sector rotation strategy, abnormal returns in the above regressions should decrease dramatically or even become insignificant after we include the anomaly.

In TableVI Panel A, we report the two-factor regression. As a benchmark, Column (1) shows that the equal-weighted sector rotation strategy has an annualized abnormal return of 8.86% (t-stat: 2.78) in CAPM. In Column (2), after we include IM, abnormal return slightly decreases to 7.26% (t-stat: 2.43). It further confirms that our strategy is different from industry momentum. From Column (3) to Column (5), we control for CIP, TSM, and LTR, respectively. The corresponding abnormal returns are 8.08%, 6.98%, and 9.92%, respectively, which are significant at 5% level. We get a similar result for the value-weighted strategy. In the four-factor regression, abnormal returns are all significant at 1% level. These results empirically suggest that sector rotation strategy cannot be explained by those anomalies, supporting our conceptual conjecture.

D. Other Variables as Indicators for Regime

We choose output gap as a proxy for the business cycle because it is a macro variable which closely tracks business cycle, in addition to its strong power to predict market returns. A natural question is whether other variables which have been shown to predict market returns

[8]We use principal component approach. It has the highest average return within their three approaches and is easy to implement.

can be good proxies. We use ten financial variables from Goyal and Welch (2008). Earning Price ratio (EP) is the log difference between earnings and prices. Dividend Price ratio (DP) is the log difference between dividend and price. Book-to-Market ratio (BM) is the ratio of book value to market value. Treasury Bills (TBL) is the three-month Treasury bill rates. Term Spread (TMS) is the log difference between yield from government bonds and Treasury bill. Default Yield Spread (DFY) is the difference between BAA and AAA-rated rated corporate bond yields. Net Equity Expansion (NTIS) is the sum of net issues. Stock Variance (SVAR) is the sum of squared daily returns. Investment to Capital ratio (IK) is the ratio of investment to capital. Consumption, wealth, income ratio (CAY) follows Lettau and Ludvigson (2001). All data are obtained from Amit Goyal's website.

By the end of year $y-1$, if the value of year $y-1$ is above the historical mean, we label the regime for year y as positive regime. Otherwise, it is defined as negative regime. We conduct sector rotation strategy as in Section III.B. As shown in Table VII, the strategy using NTIS to define regime is the only strategy which generates positive significant excess returns for both the equal-weighted and value-weighted strategy. However, the statistical significance is marginal, and the economic magnitude is only half of our main strategy. The equal-weighted strategy which uses DFY to define regime generates annualized excess return of about 5%, but the p-value is about 10%. This result is consistent with our prior that output gap is a better proxy for business cycle compared with those financial variables.

To further mitigate the concern that the profitability of sector rotation strategy based on output gap is due to data mining, we randomly generate 100,000 regime series following the approach used in Stambaugh, Yu, and Yuan (2014) and conduct sector rotation strategy based on simulated time-series. To be consistent with the regimes defined by output gap, every generated time-series has 42 positive regimes and 45 negative regimes. Results in Table VII Panel B show that the possibility a new strategy can beat our original equal-weighted strategy regarding excess return is only 0.002. The possibility to beat the value-weighted strategy regarding excess return is 0.003. Also, the possibility to beat both regarding excess return is only 0.001. It indicates that only 1 out of 1000 simulated regime series can obtain similar results as we get. The simulation results can ease the concern about data mining.

IV. Potential Explanations

In this section, we analyze some potential explanations for the profitability of our sector rotation strategy. The two broad explanations that we consider are a risk based explanation and a mispricing explanation.

A. Risk-Based Explanation

In this subsection, we consider a risk based explanation for the profitability of our sector strategy in more detail. We first consider whether the long and short portfolios are different on a variety of risk measures. Next, we check whether our sector rotation strategy is a priced in the cross-section of stock returns.

A.1. Is the Long Portfolio in the Sector Rotation Strategy More Risky?

According to the risk-return tradeoff, the significant difference between the returns of the long and the short portfolio indicates that the long portfolio is riskier than the short portfolio, thus requiring risk compensation. The results in Table IV that sector rotation strategy has significant abnormal returns after controlling for conventional risk factors do not support this explanation. To further test the risk-based explanation, we examine some other risk measures, including market beta, volatility, and higher moments of both portfolios.

As shown in Table VIII Panel A, the equal-weighted long portfolio has a market beta of 1.00 and annualized volatility of 17.72%. Similarly, the equal-weighted short portfolio has a market beta of 1.05 and annualized volatility of 18.84%. All are similar to that of the market portfolio. However, the annualized abnormal return in CAPM is 3.86% (t-stat: 2.37) for the long portfolio and -5.00% (t-stat: -2.30) for the short portfolio. It appears that the long portfolio beats the market, and the market beats the short portfolio. The skewness of the equal-weighted long portfolio is -0.73 and the kurtosis is 5.36, which are slightly lower than that of the equal-weighted short portfolio. Overall, the differences regarding those four measures between two portfolios are insignificant. Although those four measures are higher for the value-weighted long portfolio compared with the value-weighted short portfolio, the differences are too marginal to explain the return difference.

A.2. Is the Sector Rotation Strategy Return Priced?

Beyond the four measures we examine, there might be some omitted measures of risk, so we cannot completely rule out the possibility that the good performance of our sector rotation strategy is due to risk compensation. If the profitability of long-short strategy is due to risk compensation, it may capture some information about risk. We utilize the Fama-MacBeth two-stage approach to testing whether it is priced in the cross-section of stock returns. We treat the return from sector rotation strategy as a risk factor and augment it by the market factor. The test assets are 49 value-weighted industry portfolios.[9] For each industry portfolio i, we first run the following time-series regression using monthly data to get factor loadings,

$$R_{i,t} = \alpha_i + \beta_{i,factor} factor_t + \beta_{i,MKT} MKT_t + \epsilon_{i,t}. \tag{6}$$

Two approaches are used to estimate factor loadings. We first use full sample data from 1985 to 2014 to estimate fixed full-sample beta. We also use the 60-month rolling window to estimate rolling beta. With estimated factor loadings, for each month t, we run the following cross-sectional regression,

$$R_{i,t} = \alpha_i + \gamma_{factor} \hat{\beta}_{i,factor} + \gamma_{MKT} \hat{\beta}_{i,MKT} + \nu_{i,t}. \tag{7}$$

We report the time-series average of estimates in Table VIII Panel B. The price for risk of the factor is insignificant, although we find weak evidence that the market factor has a positive price for risk when using the rolling beta. All results we find cannot support the risk-based explanation.

[9] We get similar results when using 30 value-weighted industry portfolios or 25 value-weighted size and book-to-market portfolios.

B. Cash Flow Explanation

Another possible explanation for the return difference is that investors revise their expectations on firms's future cash flow growth during the holding period. Specifically, if investors upgrade their expectations regarding future cash flow growth for firms in the long portfolios and downgrade their expectations for firms in the short portfolios, the price movements due to their revisions generate the return difference between the long and the short portfolios. To test this explanation, we examine the differences in various measures related to cash flow between two portfolios, including firm fundamental measures, changes in consensus analyst forecasts, analyst forecast errors, and cumulative returns around earnings announcements.

B.1. Firm Fundamentals

No variable directly measures investors' revisions on future cash flow growth, but it is more likely for firms with better firm fundamentals, especially cash flow growth, to get upward revisions. Sales growth, the ratio between the sales of the current quarter and the sales of four quarters ago minus one, is used to measure cash flow growth as in Gomes, Kogan, and Yogo (2009). We match each firm to Fama-French 49 industry classification though SIC code. If no industry is matched, the firm is dropped from our analysis.

To compare the difference, we run the following panel regression,

$$Sale\ Growth_{i,y,q} = \alpha + \beta Long_{i,y,q} + \gamma Middle_{i,y,q} + I_i + I_y + \epsilon_{i,y,q}. \tag{8}$$

$Sale\ Growth_{i,y,q}$ is the sales growth of firm i in quarter q which ends in year y. If stock i belongs to the industries that we hold in year y, $Long_{i,y,q}$ is equal to 1. If stock i belongs to neither the industries that we long nor the industries that we short, $Middle_{i,y,q}$ is set to 1. To control the time-invariant heterogeneity in sales growth, we add firm fixed effect I_i. To control the common shock in a particular year, which causes changes in sales growth for every firm, we add year fixed effect I_y. The standard errors are clustered at the firm level.

The coefficient of interest is β. Since we add firm fixed effect, it captures the differences among companies in the long portfolio and companies in the short portfolios regarding sales growth during the holding period after controlling for the differences in average sales growth. Moreover, the differences should be more related to investors' revisions than the differences in averages. As reported in Table IX Column (1), firms in the long portfolio have 2.50% (t-stat: 2.45) higher sales growth than firms in the short portfolio. Given the fact that the median sales growth in our sample is 7.50%, the economic magnitude is significant. Firms in the middle group also have higher sales growth than the firms in the short portfolio, even though the magnitude is smaller.

To further investigate whether those firms have better operating performance, we examine profitability and Tobin's Q.[10] We run same panel regressions as that for sales growth. The result in Table IX Column (2) indicates that firms in the long portfolio have higher profitability (0.20%). The economic significance is non-negligible, given the median value in our sample is 2.30%. Similarly, as shown in Column (3), firms in the long portfolio have significantly higher Tobin's Q than firms in the short portfolio. The result further indicates that our strategy loads on growth firms, which is consistent with the negative factor loading on HML. This result may potentially explain why the long portfolio is not riskier than the short portfolio, as argued in Zhang (2005), value firms are riskier than growth firms. The results from three measures of firm fundamentals suggest that firms in the long portfolio have better fundamentals.

B.2. Revisions of Consensus Analyst Forecasts

In an efficient market, if the better performance of firms in the long portfolio is fully expected, there is no reaction from investors. To examine whether it is unexpected, we can examine the investors' revisions of cash flow growth. Upward revisions in cash flow growth would indicate unexpected better performance. However, as mentioned before, no variable can directly measure it. Instead, as argued in So (2013) that analysts' forecasts are a good

[10] Profitability is measured by operating profit divided by the total asset. Tobin's Q is measured by the market value of total asset divided by the book value of the total asset. The market value of total asset is calculated as the book value of total asset minus the book value of total assets minus the book value of common equity plus the number of common shares outstanding times the stock price by the end of the fiscal quarter.

proxy for investors' forecasts, we use changes in consensus analyst forecasts as a proxy for revisions in cash flow growth by investors.

For each firm, we get the median of analysts' EPS forecasts for the upcoming fiscal year (Fiscal Year 1) every month.[11] From the data, we can infer whether the consensus forecasts stay the same or change. In all firm-month observations, 18.30% of observation have upward revisions, and 25.20% of observations have downward revisions. We create two indicators variables I_{up} and I_{down} to measure the change. If the change is positive, I_{up} is set to 1. Otherwise, it is 0. If the change is negative, I_{down} is equal to 1. Otherwise, it is 0. Since the dependent variables are binary, we run the following linear probability model to avoid inconsistent estimation in non-linear models with fixed effects (Neyman and Scott (1948)),

$$P(I_{i,y,m} = 1) = \alpha + \beta Long_{i,y,m} + \gamma Middle_{i,y,m} + I_i + I_y + \epsilon_{i,y,m}, \tag{9}$$

where I represents for I_{up} or I_{down}. $I_{i,y,m}$ is the indicator for firm i in month m of year y. $Long_{i,y,m}$ is set to 1 if we hold the industry of stock i in that month. If stock i belongs to neither the industries that we long nor the industries that we short, $Middle_{i,y,m}$ is set to 1. I_i is firm fixed effect and I_y is year fixed effect.

The coefficient of interest in this estimation is β. In Table IX Column (4), β is 0.018 (t-stat: 4.64) when I_{up} is used as dependent variable. In the full sample, the probability of upward revision is 18.30%. Therefore, the economic magnitude is large. The result in Column (5) shows that firms in the long portfolios are also less likely to get downward revisions, but the difference is not statically significant. Those results suggest that firms in the long portfolio tend to have more upward revisions in cash flow growth, which should drive up the price for the long portfolio during our holding period. It provides a potential explanation to the profitability of the sector rotation strategy. We obtain similar results when we use logistic regressions.

[11] The results do not change if we use the mean of analysts' EPS forecasts.

B.3. Analyst Forecast Errors

To further investigate whether the differences in cash flow growth are unexpected, we examine analyst forecast errors. Since analyst forecasts are a proxy for investors's forecasts, analyst forecast errors can be a proxy for unexpected cash flow for investors. We construct analyst forecast errors as in Chang, Hartzmark, Solomon, and Soltes (2016). We obtain actual EPS in quarterly earnings announcements, and all forecasts made within 3 to 90 days before the announcements days. Analyst forecast error (Forecast Error) is defined as the difference between the actual EPS and the median forecast deflated by the stock price three days before the announcements day. A positive value of Forecast Error indicates a positive cash flow news and investors underestimate the cash flow growth. We also define two dummy variables corresponding to positive errors (I_{pos}) and negative errors (I_{neg}), respectively. In the sample, 52.8% of analyst of forecasts errors are positive, and 37.2% are negative.

For Forecast Error, we run similar panel regression as that for sales growth. As shown in Table IX Column (6), firms in the long portfolios have more positive analyst forecast errors. The coefficient for the *Long* dummy is 0.002 (t-stat: 2.13). This result suggests that investors underestimate the cash flow growth for firms in the long portfolio, leading to more positive cash flow news. For I_{pos} and I_{neg}, we run similar panel regression as that for change in consensus analyst forecasts. The results in Column (7) and (8) show that firms in the long portfolio have more positive and less negative cash flow news. The results support that the differences in cash flow growth are unexpected. The corresponding revisions in future cash flow growth as a reaction to the unexpected cash flow news can drive the return difference.

B.4. Cumulative Returns around Earnings Announcements

As we have shown that there is a systematic difference in analyst forecast errors, it would be interesting to investigate whether the cumulative returns around earnings announcements are different. If investors respond to the cash flow news and adjust their expectations, the difference in analyst forecast errors would imply that firms in the long portfolio should have higher returns around earnings announcements. To test this hypothesis, we construct five window returns around earnings announcements. [-1,i] (i=1, 3, 5, 10, 20) is the cumulative return from 1 day before earnings announcements day to i days after earnings announcements day. For each measure, we run similar panel regression as that for sales growth.

As shown in Table X Column (1), the three-day cumulative return ([-1,1]) for the firm is the long portfolio is 30 bps (t-stat: 2.78) higher than that for firm in the short portfolio, The difference goes up to 50 bps (t-stat: 3.34) after we extend the window to 7 days ([-1,5]). Although the differences in window returns cannot fully explain the return difference between two portfolios, the results support that investors respond to the cash flow news and revisions in cash flow growth does play a major role in explaining the probability of sector ration strategy.

B.5. Investor Sentiment and Sector Rotation Strategy

The results above suggest that the profitability of sector rotation strategy is due to investors' revisions in future cash flow growth as reactions to cash flow news. However, it is possible that there is overreaction/underreaction to cash flow news. For example, overreaction can widen the return difference implied by cash flow news. Therefore, the return of sector rotation strategy may be greater when mispricing is more likely. It is natural to test whether the strategy return is related to mispricing proxies. We regress monthly sector rotation strategy return on mispricing proxies as in Pastor, Stambaugh, and Taylor (2015),

$$R_{p,t} = \alpha + \beta Mispricing_t + \epsilon_t, \tag{10}$$

where the level of mispricing is proxied by Baker-Wurgler sentiment index, the Pastor-Stambaugh level of aggregate liquidity, and cross-sectional standard deviation of CRSP monthly individual stock returns. All variables are normalized. Based on our argument above, the return is higher when sentiment is higher, liquidity is lower, and cross-sectional standard deviation is higher if it is due to overreaction.

The results are reported in Table XI. The coefficients for both liquidity and cross-sectional standard deviation are insignificant. Although the coefficients for sentiment are significant for both the equal-weighted and value-weighted strategy returns, the signs are both negative, which are opposite to the expectation. We do not find evidence that there is a positive relationship between the strategy return and traditional mipricing proxies.

B.6. Why Do Investors Make Mistakes?

The current evidence is consistent with the story that investors revise their expectations on future cash flow growth. The revisions may originate from mistakenly projecting future cash flow growth. It is not surprising that investors make this kind of mistakes. Chang, Hartzmark, Solomon, and Soltes (2016) document that investor do not fully incorporate information in seasonal earnings patterns when making forecasts. It is interesting to discuss why they make systematic mistakes in projecting future cash flow growth. Tversky and Kahneman (1973) discuss that individuals are more likely to rely on recent data to make forecasts. In our case, when business cycle shifts, investors may still rely on the recent data which are not very relevant for the current regime. However, the conditional historical information should be paid more attention to. Therefore, the periods when the business cycle changes may see more mistakes.

To test this conjecture, we separate each regime into two half according to the stage of the cycle. According to the previous discussion, the return of sector rotation strategy should be higher in the first half. As shown in Table A4, the excess return in the first half is 10.66% and is 6.24% in the second half. More interestingly, after we control for Carhart four-factor model, the abnormal return is 13.25% (t-stat: 3.28) in the first half and is 4.63% in the second half (t-stat: 1.62). The first half has higher returns although the return in the second half is still non-negligible. It is also unclear to us why investors still make big mistakes in the second half. The behavioral explanation would be an interesting future research question.

V. Conclusion

Understanding how macroeconomic conditions affect industry returns is important. First, there is sparse evidence showing that macro variables predict stock returns. Second, industries have a heterogeneous sensitivity to macroeconomic conditions. We find that conditional on the business cycle, the past performance of industry portfolio is a good predictor of its future performance. This finding leads to a feasible and profitable sector rotation strategy, generating annualized excess return of 8.45%. Although practitioners have been discussing the sector rotation strategy for two decades, it is not clear how it is implemented and whether it is profitable. Our strategy provides empirical support to the profitability of sector rotation strategy and provides a simple and feasible way to implement.

Our attempt to empirically explain the profitability of the strategy also sheds light on how firms' fundamentals vary across the business cycle. We find that firms with better past performance are likely to have higher sales growth. More interestingly, our results from analysts' EPS forecast revisions and analyst forecast errors at least provide partial explanation to the profitability of sector rotation strategy. It suggests that investors do not fully incorporate this business cycle patterns in forming their forecasts, which leads to systematic underestimation for the cash flow of firms in the long portfolio. However, it is still puzzling why this systematic bias exists among investors.

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Figure 1: Time Series of Output Gap

This figure plots the time series of monthly output gap from 1927 to 2014. The construction of output gap follows Cooper and Priestley (2009). We regress the logarithm of monthly industrial production on the quadratic time trend. The residuals are defined as output gap.

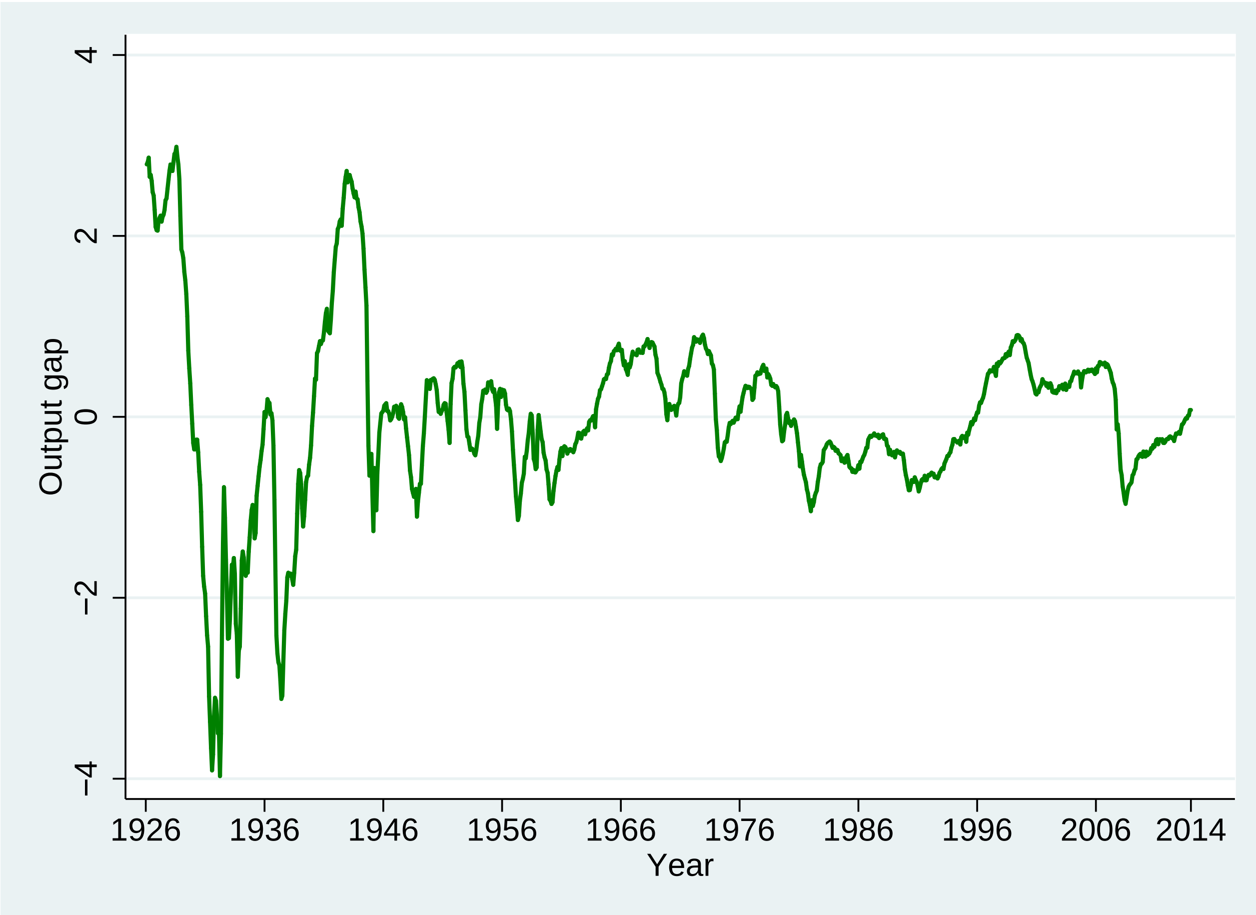
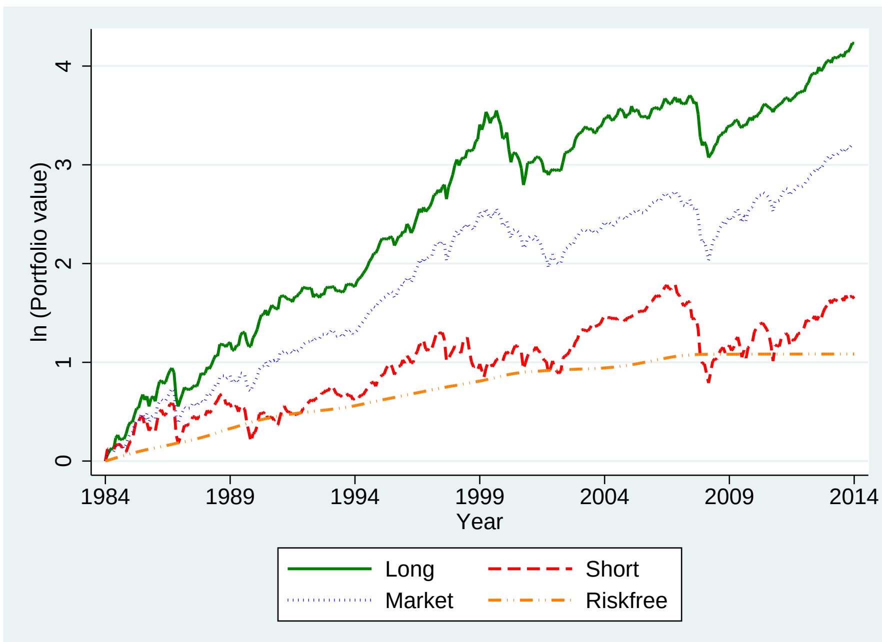


Figure 2: Portfolio Values

This figure plots portfolio values over the holding periods from 1985 to 2014 from investing \$1 in the long portfolio, short portfolio, market portfolio, and risk-free assets at the beginning of 1985. At the beginning of each year, we define the regime of this year using the most recent available output gap. We sort industries with more than 30 stocks based on the Sharpe Ratio calculated from past years with the same regime starting from 1928. The long portfolio includes industries in the highest decile and the short portfolio includes industries in the lowest decile. In the upper figure, the long and short portfolios are equal-weighted. In the lower figure, the long and short portfolios are value-weighted.



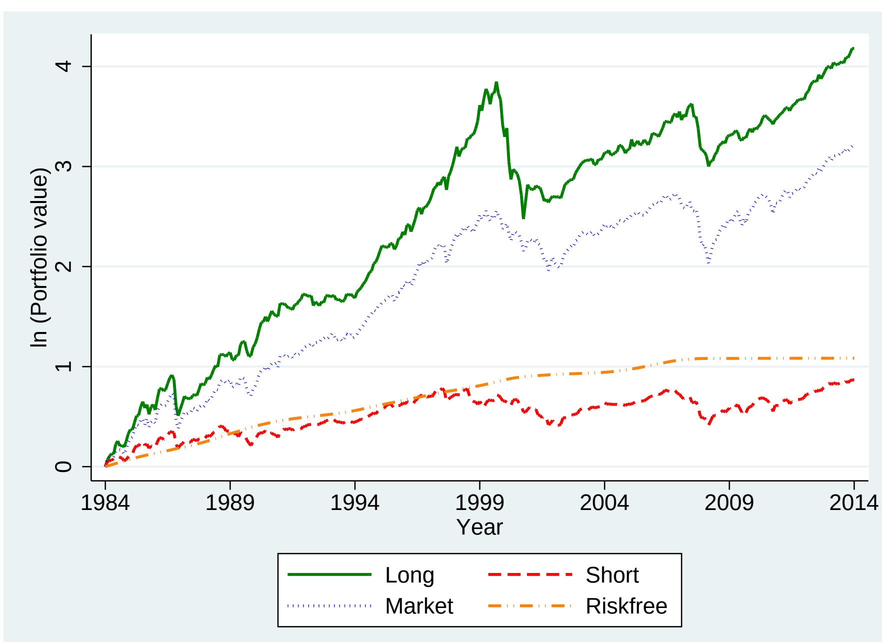


Table I: Summary Statistics for Annualized Excess Returns of Industry Portfolios

This table presents the summary statistics for annual excess returns of 40 industry portfolios used in our analysis from 1927 to 2014. We obtain 49 value-weighted industry portfolios from Kenneth French's Data Library and exclude 9 industry portfolios without full time-series of returns. The regime of year y is defined based on the sign of output gap (Cooper and Priestley (2009)) on November of year $y-1$. The mean excess return and Sharpe Ratio for full sample, positive regime, and negative regime are reported. Returns are in percentage points.

	Full Sample		Positive Regime		Negative Regime		
	Mean	Sharpe Ratio	Mean	Sharpe Ratio	Mean	Sharpe Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(6)-(4)
Agric	8.28	0.29	5.22	0.21	11.14	0.35	0.15
Food	8.68	0.48	3.95	0.23	13.10	0.71	0.47
Beer	11.95	0.35	6.83	0.20	16.74	0.50	0.30
Smoke	10.62	0.49	7.75	0.36	13.30	0.62	0.27
Toys	10.16	0.27	3.84	0.12	16.05	0.39	0.27
Fun	12.61	0.36	11.32	0.31	13.81	0.41	0.10
Books	9.92	0.30	12.15	0.31	7.83	0.28	-0.03
Hshld	7.95	0.38	3.89	0.17	11.73	0.64	0.47
Clths	8.94	0.32	3.73	0.13	13.81	0.53	0.40
MedEq	10.29	0.41	8.97	0.36	11.51	0.46	0.10
Drugs	10.11	0.48	5.77	0.28	14.16	0.66	0.38
Chems	9.27	0.38	3.20	0.15	14.93	0.56	0.40
Txtls	9.73	0.31	1.99	0.06	16.95	0.55	0.48
BldMt	8.88	0.34	4.45	0.18	13.01	0.48	0.30
Cnstr	10.00	0.27	14.18	0.39	6.09	0.17	-0.22
Steel	7.83	0.25	6.02	0.20	9.51	0.29	0.10
Mach	9.24	0.35	6.38	0.26	11.91	0.42	0.16
ElcEq	10.56	0.40	10.30	0.37	10.80	0.44	0.08
Autos	11.09	0.31	3.25	0.10	18.42	0.48	0.37
Aero	14.15	0.36	11.39	0.22	16.72	0.65	0.43
Ships	9.26	0.28	6.91	0.27	11.45	0.30	0.03
Mines	9.10	0.30	8.65	0.28	9.52	0.33	0.05
Coal	9.65	0.28	16.19	0.44	3.54	0.11	-0.33
Oil	9.63	0.44	8.98	0.39	10.25	0.49	0.11
Util	7.43	0.35	7.19	0.33	7.66	0.36	0.02

	Full Sample		Positive Regime		Negative Regime		
	Mean	Sharpe Ratio	Mean	Sharpe Ratio	Mean	Sharpe Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(6)-(4)
Telcm	7.43	0.39	2.96	0.16	11.59	0.62	0.46
BusSv	8.82	0.29	7.57	0.27	9.99	0.32	0.05
Hardw	12.27	0.39	11.10	0.32	13.36	0.47	0.15
Chips	11.38	0.32	7.56	0.21	14.95	0.43	0.22
LadEq	9.90	0.40	7.63	0.29	12.02	0.53	0.25
Boxes	9.62	0.43	6.45	0.31	12.57	0.52	0.21
Trans	7.82	0.32	3.55	0.16	11.81	0.45	0.29
Whlsl	9.00	0.30	6.27	0.20	11.54	0.41	0.21
Rtail	9.63	0.39	4.36	0.17	14.54	0.64	0.47
Meals	11.10	0.34	12.10	0.31	10.17	0.40	0.09
Banks	12.07	0.39	8.24	0.29	15.64	0.46	0.17
Insur	7.70	0.35	3.30	0.14	11.80	0.56	0.42
RlEst	8.37	0.21	10.29	0.24	6.57	0.18	-0.06
Fin	10.45	0.36	8.67	0.28	12.11	0.43	0.15
Other	6.72	0.22	-0.33	-0.01	13.31	0.43	0.44

Table II: Description for Industry Portfolios

This table describes the components of 40 industry portfolios used in our analysis from 1985 to 2014. We obtain 49 value-weighted industry portfolios from Kenneth French's Data Library and exclude 9 industries without full time-series of returns from 1927 to 2014. For each month, we obtain the number of stocks and calculate the percentage of total market capitalization for each industry. We report the time-series average. We also report the minimum number of stocks during the sample period for each industry.

	Ave. Num. of Stocks	Min. Num. of Stocks	% of ME		Ave. Num. of Stocks	Min. Num. of Stocks	% of ME
Agric	15.42	7	0.18	Ships	8.57	6	0.12
Food	78.56	49	2.64	Mines	18.70	8	0.30
Beer	14.01	9	1.76	Coal	7.39	2	0.11
Smoke	5.13	4	1.06	Oil	189.09	130	7.23
Toys	40.88	16	0.23	Util	147.89	88	4.96
Fun	74.11	41	0.96	Telcm	120.54	78	6.66
Books	44.78	14	1.05	BusSv	264.38	162	1.92
Hshld	86.11	40	2.60	Hardw	149.51	60	4.41
Clths	68.25	32	0.61	Chips	276.90	188	4.07
MedEq	159.33	105	1.36	LadEq	111.44	62	0.79
Drugs	249.41	80	7.53	Boxes	14.81	8	0.30
Chems	84.13	66	2.54	Trans	105.35	70	1.89
Txtls	28.14	7	0.16	Whlsl	189.11	94	1.25
BldMt	92.96	47	0.92	Rtail	249.54	160	6.25
Cnstr	60.40	40	0.41	Meals	94.89	53	1.07
Steel	64.91	39	0.76	Banks	519.17	212	8.18
Mach	163.07	99	1.95	Insur	173.86	104	4.84
ElcEq	81.01	50	1.48	RlEst	35.88	17	0.12
Autos	64.03	48	1.78	Fin	303.94	87	3.20
Aero	22.08	15	1.20	Other	76.16	41	2.10

Table III: Industry Excess Returns and Regime Sharpe Ratio

This table reports the estimates from panel regressions over the sample periods from 1985 to 2014. The analysis is conducted at annual (monthly) frequency in Panel A (Panel B). The dependent variable is the industry excess return in a year (month). Regime_SR is the Sharpe Ratio calculated from past periods with the same regime. Historical_SR is the Sharpe Ratio calculated from all historical data. Opp_Regime_SR is the Sharpe Ratio calculated from past periods with the opposite regime. The regime of current period is defined according to the sign of the most recent output gap. The independent variables include industry characteristics: the logarithm of average market capitalization (Log(Size)), aggregate book-to-market ratio (BM), and past one year return (Ret_212). We also include factor loading on the Fama-French three-factor model estimated from past 60-month rolling window: β_{MKT}, β_{SMB}, and β_{HML}. We only use well-diversified industry portfolios (more than 30 stocks) from Column (1) to Column (5), and include all industry portfolios from Column (6) to Column (10). Time fixed effect is included in the regression. t-statistics based on robust standard errors with clustering at the time and industry level are reported in parenthesis. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Panel A: Annual Frequency

	Ret									
	Well-Diversified Portfolios					All Portfolios				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Regime_SR	0.167**			0.182***	0.174***	0.166**			0.160**	0.186**
	(2.52)			(3.02)	(3.00)	(2.10)			(2.26)	(2.30)
Historical_SR		0.135					0.073			
		(1.14)					(0.72)			
Opp_Regime_SR			-0.090					-0.122		
			(-1.64)					(-1.43)		
Log(Size)				-0.013					-0.003	
				(-1.03)					(-0.37)	
BM				0.025					0.008	
				(1.58)					(0.34)	
Ret_212				0.070					0.060	
				(0.98)					(0.94)	
β_MKT					0.055					0.045
					(1.38)					(1.05)
β_SMB					-0.020					-0.007
					(-1.34)					(-0.36)
β_HML					0.012					0.039*
					(0.52)					(1.73)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	926	926	926	926	926	1,200	1,200	1,200	1,200	1,200
R-squared	0.54	0.54	0.54	0.55	0.55	0.48	0.48	0.48	0.49	0.49

Panel B: Monthly Frequency										
	Ret									
	Well-Diversified Portfolios					All Portfolios				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Regime_SR	0.037**			0.030**	0.041***	0.041**			0.035*	0.050**
	(2.28)			(2.56)	(2.69)	(2.02)			(1.84)	(2.39)
Historical_SR		0.034					0.020			
		(1.24)					(0.76)			
Opp_Regime_SR			-0.016					-0.028		
			(-1.32)					(-1.27)		
Log(Size)				-0.001					-0.000	
				(-0.96)					(-0.58)	
BM				0.001					0.000	
				(0.67)					(0.17)	
Ret_212				0.013*					0.010	
				(1.74)					(1.60)	
β_MKT					0.002					0.003
					(0.86)					(0.95)
β_SMB					0.000					0.000
					(0.04)					(0.21)
β_HML					0.001					0.003*
					(0.59)					(1.85)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	11,090	11,090	11,090	11,090	11,090	14,400	14,400	14,400	14,400	14,400
R-squared	0.60	0.60	0.60	0.61	0.60	0.54	0.54	0.54	0.54	0.54

Table IV: Performance of Sector Rotation Strategy

This table reports the performance of sector rotation strategy from 1985 to 2014. At the beginning of each year, we define the regime of this year according to the sign of the most recent output gap. In Panel A, we sort industries based on the Sharpe Ratio calculated from past years with the same regime. In Panel B, we sort industries based on the Sharpe Ratio calculated from all past years. In Panel C, we sort industries based on the Sharpe Ratio calculated from past years with the opposite regime. Industry portfolios with more than 30 firms are included. Within each decile, we create both equal-weighted and value-weighted portfolios. We long industries in the highest decile and short industries in the lowest decile. The annualized excess return and alphas from CAPM, Fama-French three-factor model (FF3), Carhart four-factor model (Carhart4), Fama-French three-factor model augmented by durability factor (FF3+DUR), Pastor-Stambaugh four-factor model (PS4), Hou-Xue-Zhang q-factor model (HXZ4), and Fama-French five-factor model (FF5) are reported. Excess return and alphas are in percentage points. t-statistics reported in the parenthesis are calculated using the Newey-West standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Exc. Ret.	CAPM	FF3	Carhart4	FF3+DUR	PS4	HXZ4	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Sort on the Sharpe Ratio Computed from the Same Regime								
Equal-Weighted								
Low	3.71	-5.00**	-6.92***	-5.76***	-7.17***	-7.23***	-8.85***	-8.60***
	(0.99)	(-2.30)	(-3.82)	(-3.18)	(-3.59)	(-4.04)	(-4.44)	(-5.13)
High	12.16***	3.86**	4.98***	4.19***	5.39***	4.54***	5.61***	5.43***
	(3.58)	(2.37)	(3.32)	(2.85)	(3.24)	(2.92)	(3.37)	(3.47)
H-L	8.45***	8.86***	11.91***	9.95***	12.56***	11.78***	14.46***	14.02***
	(2.86)	(2.78)	(4.44)	(3.94)	(4.26)	(4.37)	(4.78)	(5.28)
Value-Weighted								
Low	4.83	-3.82**	-4.94***	-4.16**	-6.19***	-4.83**	-6.52***	-5.82***
	(1.32)	(-2.00)	(-2.64)	(-2.13)	(-2.69)	(-2.57)	(-3.46)	(-3.44)
High	12.51***	3.75	6.17***	5.58***	6.94***	5.90***	9.71***	8.54***
	(3.20)	(1.50)	(3.28)	(3.15)	(3.35)	(3.11)	(4.64)	(4.60)
H-L	7.68**	7.58**	11.11***	9.75***	13.13***	10.74***	16.23***	14.37***
	(2.36)	(2.10)	(3.76)	(3.39)	(3.95)	(3.67)	(4.92)	(5.05)

	Exc. Ret.	CAPM	FF3	Carhart4	FF3+DUR	PS4	HXZ4	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Sort on the Sharpe Ratio Computed from All Past Years								
				Equal-Weighted				
Low	6.36	-2.92	-4.84***	-4.32***	-3.85**	-4.90***	-5.83***	-5.52***
	(1.64)	(-1.32)	(-2.99)	(-2.65)	(-2.09)	(-2.96)	(-3.43)	(-3.38)
High	8.85***	2.06	2.83**	1.89	2.55	2.78**	1.68	1.57
	(3.18)	(1.43)	(2.14)	(1.46)	(1.56)	(2.06)	(1.14)	(1.11)
H-L	2.49	4.98	7.68***	6.21***	6.41**	7.68***	7.51***	7.08***
	(0.83)	(1.61)	(3.39)	(2.80)	(2.44)	(3.33)	(2.99)	(3.08)
				Value-Weighted				
Low	6.15	-3.18	-4.14**	-3.74*	-3.70	-3.54*	-4.94**	-4.51**
	(1.63)	(-1.63)	(-2.24)	(-1.88)	(-1.62)	(-1.85)	(-2.44)	(-2.36)
High	8.81***	1.97	2.63**	0.99	2.91*	2.55*	0.96	1.31
	(3.05)	(1.31)	(1.89)	(0.73)	(1.70)	(1.80)	(0.58)	(0.85)
H-L	2.66	5.14*	6.77***	4.72*	6.62**	6.09**	5.90**	5.82**
	(0.98)	(1.89)	(2.78)	(1.94)	(2.24)	(2.41)	(2.23)	(2.33)
Panel C: Sort on the Sharpe Ratio Computed from the Opposite Regime								
				Equal-Weighted				
Low	10.72***	1.84	-0.17	0.02	-0.37	0.09	-2.60	-2.01
	(2.78)	(0.87)	(-0.11)	(0.01)	(-0.21)	(0.06)	(-1.46)	(-1.33)
High	6.00**	-1.01	-1.79	-1.84	-2.09	-1.01	-5.78***	-6.03***
	(2.00)	(-0.48)	(-0.88)	(-0.86)	(-0.95)	(-0.49)	(-2.80)	(-3.27)
H-L	-4.72*	-2.86	-1.62	-1.86	-1.73	-1.10	-3.18	-4.02
	(-1.77)	(-1.09)	(-0.67)	(-0.73)	(-0.69)	(-0.44)	(-1.20)	(-1.61)
				Value-Weighted				
Low	10.93***	2.38	0.91	0.29	0.82	1.04	-2.11	-0.35
	(3.13)	(1.35)	(0.62)	(0.20)	(0.45)	(0.69)	(-1.39)	(-0.23)
High	5.12	-1.72	-1.88	-1.95	-1.74	-1.18	-5.11**	-5.64***
	(1.64)	(-0.77)	(-0.86)	(-0.85)	(-0.74)	(-0.52)	(-2.23)	(-2.75)
H-L	-5.81**	-4.10	-2.79	-2.24	-2.56	-2.22	-3.00	-5.29**
	(-2.12)	(-1.48)	(-1.06)	(-0.82)	(-0.88)	(-0.81)	(-1.02)	(-2.00)

Table V: Performance of Sector Rotation Strategy: Robustness Check

This table reports the performance of sector rotation strategy using different evaluation approach, including all industry portfolios, applying different industry classification (30 industry portfolios), or testing different sample period. Panel A allows time-varying factor loadings across regimes. Panel B drops the requirement for the number of stocks in industry portfolios. Panel C uses 30 value-weighted industry portfolios. Panel D examines the holding period from 1985 to 2007. At the beginning of each year, we define the regime of this year according to the sign of the most recent output gap. We sort industries based on the Sharpe Ratio calculated from past years with the same regime. Industry portfolios with more than 30 firms are included. Within each decile, we create both equal-weighted and value-weighted portfolios. We long industries in the highest decile and short industries in the lowest decile. The annualized excess return and alphas from CAPM, Fama-French three-factor model (FF3), Carhart four-factor model (Carhart4), Fama-French three-factor model augmented by durability factor (FF3+DUR), Pastor-Stambaugh four-factor model (PS4), Hou-Xue-Zhang q-factor model (HXZ4), and Fama-French five-factor model (FF5) are reported. Excess return and alphas are in percentage points. t-statistics reported in the parenthesis are calculated using the Newey-West standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Exc. Ret.	CAPM	FF3	Carhart4	FF3+DUR	PS4	HXZ4	FF5
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Time-Varying Factor Loadings							
Equal-Weighted							
8.45***	9.77***	11.61***	9.67***	11.54***	11.64***	11.63***	11.81***
(2.86)	(3.23)	(4.56)	(4.02)	(3.89)	(4.69)	(3.84)	(4.43)
Value-Weighted							
7.68**	8.62**	11.22***	9.82***	12.14***	10.81***	12.82***	11.94***
(2.36)	(2.54)	(4.04)	(3.48)	(3.53)	(4.03)	(3.79)	(3.99)
Panel B: Include All Industry Portfolios							
Equal-Weighted							
5.52*	6.68**	9.61***	6.97**	9.01***	9.38***	10.93***	11.37***
(1.75)	(2.02)	(3.17)	(2.30)	(2.93)	(3.03)	(3.21)	(3.74)
Value-Weighted							
6.87**	7.49**	11.24***	9.57***	10.18***	11.04***	15.42***	13.42***
(2.05)	(2.03)	(3.83)	(3.19)	(3.15)	(3.71)	(4.33)	(4.45)
Panel C: 30 Industry Portfolios							
Equal-Weighted							
7.43**	7.36**	10.91***	9.12***	8.47***	11.01***	14.36***	13.01***
(2.48)	(2.30)	(4.13)	(3.46)	(2.98)	(3.99)	(4.35)	(4.79)
Value-Weighted							
8.12**	7.06**	10.76***	10.11***	7.88**	10.56***	16.56***	13.35***
(2.46)	(2.03)	(3.56)	(3.14)	(2.35)	(3.36)	(4.59)	(4.16)
Panel D: 1985-2007							
Equal-Weighted							
8.89**	7.81**	12.49***	9.50***	12.56***	11.81***	13.86***	14.29***
(2.57)	(2.06)	(4.16)	(3.34)	(4.26)	(3.90)	(3.81)	(4.86)
Value-Weighted							
8.89**	7.39*	13.10***	11.52***	13.13***	11.94***	17.86***	15.95***
(2.24)	(1.66)	(3.91)	(3.33)	(3.95)	(3.51)	(4.46)	(4.89)

Table VI: Sector Rotation Strategy and Related Anomalies

This table examines whether sector rotation strategy can be explained by related anomalies from 1985 to 2014. At the beginning of each year, we define the regime of this year according to the sign of the most recent output gap. We sort industries based on the Sharpe Ratio calculated from past years with the same regime. Industry portfolios with more than 30 firms are included. Within each decile, we create both equal-weighted and value-weighted portfolio. We long industries in the highest decile and short industries in the lowest decile. In Panel A, we report α from regressing the strategy return on market factor (MKT) and one of the related anomalies. In Panel B, we report α from regressing the strategy return on Fama-French three-factor model plus one related anomaly. Related anomalies include industry momentum (IM), sector rotation strategy based on cross-industry predictability (CIP), time-series momentum (TSM), and long-term reversal (LTR). α are annualized and in percentage points. t-statistics reported in the parenthesis are calculated using the Newey-West standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Two-Factor Regression				
CAPM	MKT+IM	MKT+CIP	MKT+TSM	MKT+LTR
(1)	(2)	(3)	(4)	(5)
		Equal-Weighted		
8.86***	7.26**	8.08**	6.98**	9.92***
(2.78)	(2.43)	(2.52)	(2.11)	(3.34)
		Value-Weighted		
7.58**	6.28**	6.99*	5.76	8.57**
(2.10)	(1.96)	(1.88)	(1.62)	(2.59)
Panel B: Four-Factor Regression				
FF3	FF3+IM	FF3+CIP	FF3+TSM	FF3+LTR
(1)	(2)	(3)	(4)	(5)
		Equal-Weighted		
11.91***	10.40***	11.28***	10.80***	12.02***
(4.44)	(4.03)	(4.23)	(3.74)	(4.48)
		Value-Weighted		
11.11***	10.10***	10.66***	10.04***	11.24***
(3.76)	(3.51)	(3.53)	(3.32)	(3.79)

Table VII: Other Variables as Indicators for Regime

Panel A reports the performance of sector rotation strategy from 1985 to 2014 when using financial variables obtained from Goyal and Welch (2008) to define regimes. At the beginning of each year, we define the regime of this year by comparing last year's value with the historical mean. We sort industries based on the Sharpe Ratio calculated from past years with the same regime. Industry portfolios with more than 30 firms are included. Within each decile, we create both equal-weighted and value-weighted portfolios. We long industries in the highest decile and short industries in the lowest decile. The annualized excess return in percentage points are reported. t-statistics reported in the parenthesis are calculated using the Newey-West standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Panel B reports the possibility that a sector rotation strategy based on a randomly generated regime series beats our original strategy. We generate 100,000 regime series. Each of them has 45 negative regimes and 42 positive regimes. We use the generated regime series to conduct sector rotation strategy and compare it with our original strategy.

Panel A: Financial Variables as Indicators for Regime

	EP	DP	BM	TBL	TMS	DFY	NTIS	SVAR	IK	CAY
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Equal-Weighted										
Exc. Ret.	2.58	1.10	1.48	-0.80	2.67	4.93*	4.51**	3.60	0.74	3.48
t-stat	(1.16)	(0.39)	(0.59)	(-0.32)	(1.00)	(1.65)	(1.98)	(1.34)	(0.25)	(1.41)
Value-Weighted										
Exc. Ret.	2.69	-5.63	5.77	2.47	2.66	5.01	4.47*	3.18	4.94	3.64
t-stat	(1.19)	(-0.11)	(1.05)	(0.37)	(1.00)	(1.63)	(1.93)	(1.16)	(1.25)	(1.52)

Panel B: Possibility That a Randomly Generated Regime Series Can Obtain Better Results

EW Ret	EW t-stat	VW Ret	VW t-stat	Both Ret	Both t-stat	All
(1)	(2)	(3)	(4)	(5)	(6)	(7)
0.002	0.006	0.003	0.011	0.001	0.004	0.001

Table VIII: Risk and Sector Rotation Strategy

Panel A reports various risk measures, including market beta, annualized volatility, skewness and kurtosis for the long and short portfolio separately from 1985 to 2014. At the beginning of each year, we define the regime of this year according to the sign of the most recent output gap. We sort industries based on the Sharpe Ratio calculated from past years with the same regime. Industry portfolios with more than 30 firms are included. Within each decile, we create both equal-weighted and value-weighted portfolios. We long industries in the highest decile and short industries in the lowest decile. Panel B reports the second-stage results from Fama-MacBeth regression. We use the long-short sector rotation strategy return and market excess return as risk factors. Factor loadings are estimated using full sample or 60-month rolling window. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Risk of the Long and Short Portfolios				
	Equal-Weighted		Value-Weighted	
	Long	Short	Long	Short
	(1)	(2)	(3)	(4)
Market Beta	1.00	1.05	1.05	1.03
Volatility	17.72%	18.84%	20.24%	18.77%
Skewness	-0.73	-0.85	-0.96	-0.61
Kurtosis	5.36	5.94	6.87	4.96
Panel B: Long-Short Portfolios as Risk Factor				
	Equal-Weighted Factor		Value-Weighted Factor	
	Fixed Beta	Rolling Beta	Fixed Beta	Rolling Beta
	(1)	(2)	(3)	(4)
β_factor	0.003	-0.001	0.004	-0.003
	(0.79)	(-0.49)	(0.86)	(-0.95)
β_MKT	0.001	0.005*	0.001	0.006*
	(0.34)	(1.67)	(0.21)	(1.82)
Cons.	0.007**	0.001	0.007***	0.001
	(2.53)	(0.49)	(2.73)	(0.26)
Number of Periods	360	300	360	300
Average $\bar{R}^2$	0.12	0.14	0.12	0.14

Table IX: Firm Fundamentals and Analyst Forecasts

This table reports the results from firm-level panel regressions. The dependent variables are sales growth, profitability, Tobin's Q, indicator of upward change in monthly analysts' consensus forecasts (I_up), indicator of downward change in monthly analysts' consensus forecasts (I_down), analyst forecast errors from quarterly earnings announcement (Forecast Error), indicator of positive analyst forecast errors (I_pos), and indicator of negative analyst forecast errors (I_neg). $Long_{i,y}$ is set to 1 if stock i belongs to the industries that we long in year y. $Middle_{i,y}$ is set to 1 if stock i belongs to neither the industries that we long nor the industries that we short. Both firm fixed effect and year fixed effect are included in the regression. t-statistics reported in the parenthesis are calculated using standard errors clustered at firm level. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Firm Fundamentals			**Change in Consensus Forecasts**		**Analyst Forecast Errors**		
	Sales Growth	Profitability	Tobin's Q	I_up	I_down	Forecast Error	I_pos	I_neg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	0.025**	0.002	0.176***	0.018***	-0.001	0.002**	0.025***	-0.014*
	(2.45)	(1.61)	(5.19)	(4.64)	(-0.17)	(2.13)	(2.86)	(-1.72)
Middle	0.012	0.001	0.064***	0.018***	-0.002	0.001	0.021***	-0.017**
	(1.59)	(1.45)	(2.70)	(5.95)	(-0.63)	(1.00)	(3.01)	(-2.52)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	542,761	540,200	607,955	1,146,095	1,146,095	310,027	310,027	310,027
R-squared	0.177	0.619	0.564	0.05	0.06	0.217	0.106	0.127

Table X: Cumulative Returns around Earnings Announcements

This table reports the cumulative returns around earnings announcements. [-1,t] is the cumulative return from one day before the earnings announcement day to t day after the earnings announcement day. $Long_{i,y}$ is set to 1 if stock i belongs to the industries that we long in year y. $Middle_{i,y}$ is set to 1 if stock i belongs to neither the industries that we long nor the industries that we short. Both firm fixed effect and year fixed effect are included in the regression. t-statistics reported in the parenthesis are calculated using standard errors clustered at firm level. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	[-1,1]	[-1,3]	[-1,5]	[-1,10]	[-1,20]
	(1)	(2)	(3)	(4)	(5)
Long	0.003***	0.004***	0.005***	0.005***	0.005**
	(2.78)	(2.94)	(3.34)	(2.76)	(2.36)
Middle	0.002**	0.003***	0.003***	0.003**	0.002
	(2.30)	(2.94)	(2.86)	(2.15)	(1.12)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	441,997	444,155	446,655	450,969	455,147
R-squared	0.047	0.048	0.050	0.050	0.053

Table XI: Regression of Sector Rotation Strategy Returns on Mispricing Proxies

This table reports the time-series regression of sector rotation strategy returns on contemporaneous mispricing proxies as in Pastor, Stambaugh, and Taylor (2015). Sentiment is the Baker-Wurgler sentiment index. Liquidity is the Pastor-Stambaugh levels of aggregate liquidity. Cross_Std is the cross-sectional standard deviation of all monthly CRSP individual stock returns. All variables are normalized. t-statistics reported in the parenthesis are calculated using the Newey-West standard errors. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

		Ret					
	Expected	Equal-Weighted			Value-Weighted		
		(1)	(2)	(3)	(4)	(5)	(6)
Sentiment	+	-0.0076**			-0.0091*		
		(-2.39)			(-1.93)		
Liquidity	-		-0.0013			0.0010	
			(-0.49)			(0.32)	
Cross_Std	+			0.0014			0.0056
				(0.39)			(1.31)
Observations		312	360	360	312	360	360
R-squared		0.03	0.00	0.00	0.03	0.00	0.01

Figure A1: Proportion of Stocks Covered

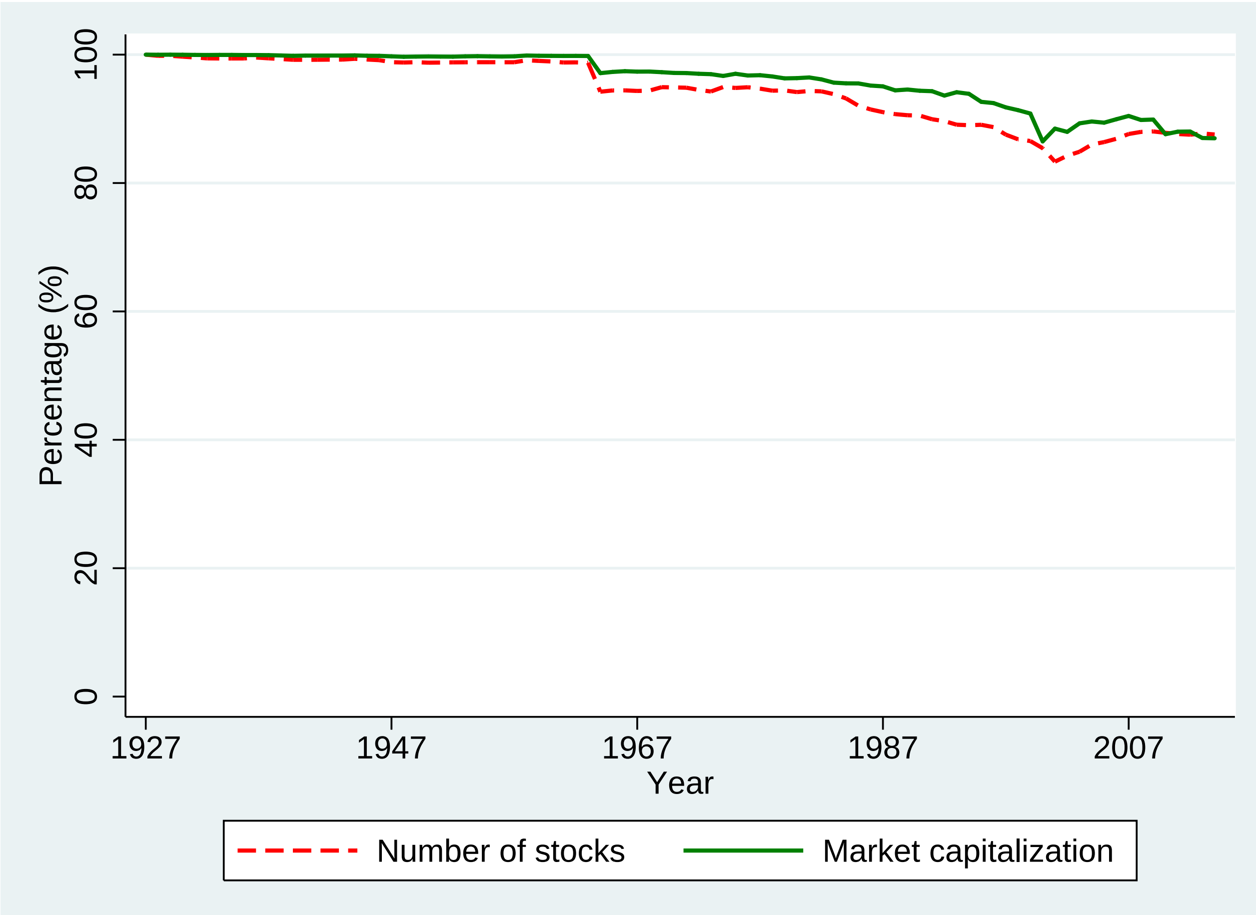


Figure A2: Number of Stocks in the Long and Short Portfolios

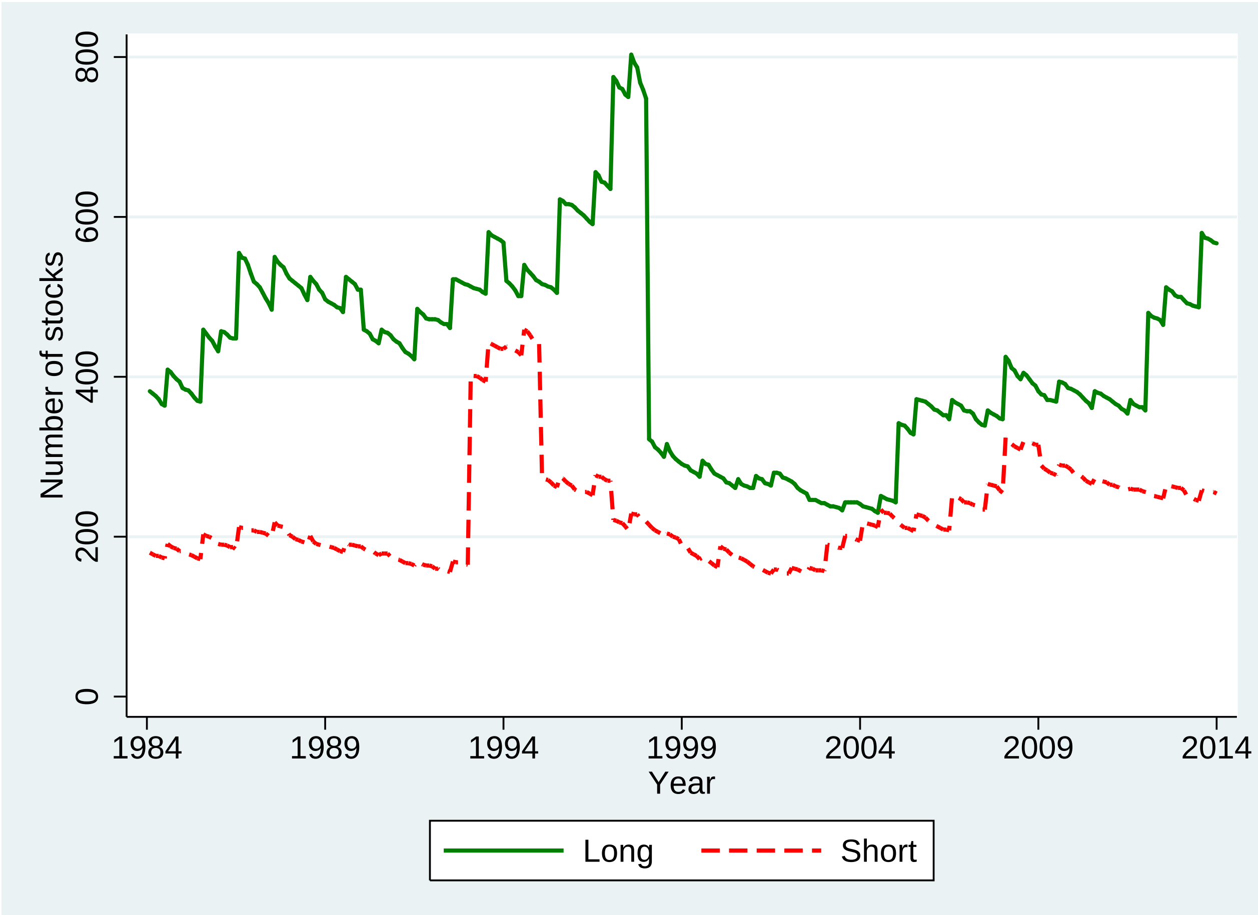


Figure A3: Filter and the Performance of Sector Rotation Strategy

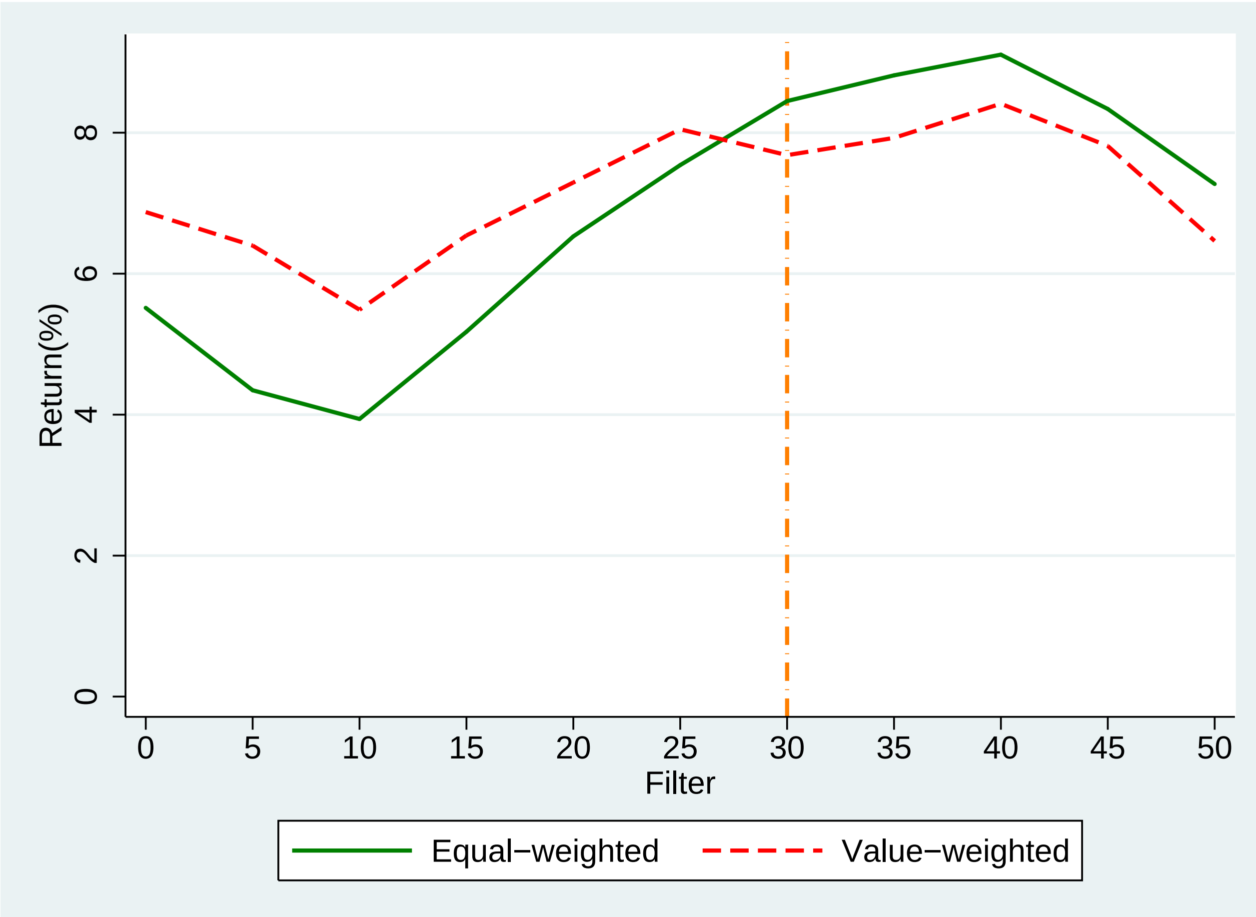


Table A1: Components of the Long and Short Portfolios

Holding Period	Short			Long		
1985	Books	Cnstr	RlEst	Food	Telcm	Rtail
1986	Books	Cnstr	RlEst	Food	Telcm	Rtail
1987	Books	Cnstr	RlEst	Food	Drugs	Rtail
1988	Books	Cnstr	RlEst	Food	Drugs	Rtail
1989	Books	Cnstr	RlEst	Food	Drugs	Rtail
1990	Books	Cnstr	RlEst	Food	Drugs	Rtail
1991	Books	Cnstr	RlEst	Food	Hshld	Rtail
1992	Books	Cnstr	RlEst	Food	Hshld	Rtail
1993	Books	Cnstr	RlEst	Food	Hshld	Rtail
1994	Books	Cnstr	BusSv	Food	Hshld	Rtail
1995	Steel	Autos	Insur	MedEq	Drugs	Cnstr
1996	Steel	Autos	Other	MedEq	Drugs	Cnstr
1997	Steel	Autos	Other	MedEq	Drugs	Cnstr
1998	Clths	Txtls	Other	MedEq	Drugs	Hardw
1999	Clths	Txtls	Other	Books	ElcEq	Hardw
2000	Clths	Txtls	Other	Books	ElcEq	Hardw
2001	Toys	Clths	Other	Books	ElcEq	Hardw
2002	Toys	Clths	Other	Books	MedEq	Cnstr
2003	Clths	Autos	Other	Books	MedEq	Cnstr
2004	Hshld	Trans	Other	Books	MedEq	Cnstr
2005	Hshld	Telcm	Other	Books	MedEq	Cnstr
2006	Autos	Telcm	Other	MedEq	Cnstr	Oil
2007	Autos	Telcm	Other	MedEq	Cnstr	Oil
2008	Autos	Telcm	Other	MedEq	Cnstr	Oil
2009	Cnstr	BusSv	Meals	Food	Hshld	Drugs
2010	Cnstr	Steel	BusSv	Food	Hshld	Drugs
2011	Cnstr	Steel	BusSv	Food	Hshld	Drugs
2012	Cnstr	Steel	BusSv	Food	Hshld	Drugs
2013	Cnstr	Steel	BusSv	Food	Drugs	Rtail
2014	Cnstr	Steel	BusSv	Food	Drugs	Rtail

Table A2: Factor Loadings

	CAPM (1)	FF3 (2)	Cahart4 (3)	FF3+DUR (4)	PS4 (5)	HXZ4 (6)	FF5 (7)
Panel A: Equal-Weighted							
MKT	-0.05	-0.15**	-0.10	-0.05	-0.14**	-0.17***	-0.20***
	(-0.61)	(-2.34)	(-1.53)	(-0.64)	(-2.22)	(-2.69)	(-3.23)
SMB		-0.24***	-0.25***	-0.20**	-0.28***	-0.27**	-0.33***
		(-2.66)	(-3.36)	(-2.02)	(-3.05)	(-2.01)	(-3.46)
HML		-0.73***	-0.67***	-0.71***	-0.70***		-0.53***
		(-6.21)	(-5.07)	(-5.38)	(-6.00)		(-3.89)
MOM			0.20***				
			(2.94)				
DUR				-0.18*			
				(-1.87)			
LIQ					0.02		
					(0.32)		
IA						-0.94***	
						(-6.26)	
ROE						-0.03	
						(-0.24)	
RMW							-0.23*
							(-1.83)
CMA							-0.30
							(-1.59)
Panel B: Value-Weighted							
MKT	0.01	-0.14**	-0.11	-0.11	-0.13*	-0.20***	-0.22***
	(0.13)	(-1.96)	(-1.53)	(-1.13)	(-1.79)	(-3.37)	(-3.24)
SMB		-0.04	-0.04	0.05	-0.09	-0.16	-0.16
		(-0.35)	(-0.46)	(0.40)	(-0.85)	(-1.00)	(-1.30)
HML		-0.83***	-0.78***	-0.86***	-0.83***		-0.56***
		(-4.98)	(-3.94)	(-4.19)	(-4.93)		(-3.70)
MOM			0.14				
			(1.26)				
DUR				-0.08			
				(-0.64)			
LIQ					0.06		
					(0.75)		
IA						-1.22***	
						(-5.37)	
ROE						-0.23	
						(-1.57)	
RMW							-0.32**
							(-2.12)
CMA							-0.48*
							(-1.87)

Table A3: Summary Statistics for Firm-Level Measures

	N	Mean	SD	25th	Median	75th
Firm Fundamentals						
Sales Growth	542,761	0.182	0.636	-0.048	0.075	0.236
Profitability	540,200	0.014	0.060	0.004	0.023	0.043
Tobin's Q	607,955	1.935	1.698	1.039	1.326	2.079
Change in Consensus Forecasts						
I_up	1,146,095	0.183	0.387	0	0	0
I_down	1,146,095	0.252	0.434	0	0	1
Analyst Forecast Errors						
Forecast Error	310,027	-0.005	0.045	0	0	0
I_pos	310,027	0.528	0.499	0	1	1
I_neg	310,027	0.372	0.483	0	0	1
Cumulative Returns						
$[-1, 1]$	441,997	0.004	0.101	-0.038	0.001	0.042
$[-1, 3]$	444,155	0.004	0.116	-0.048	0.001	0.049
$[-1, 5]$	446,655	0.005	0.128	-0.053	0.001	0.054
$[-1, 10]$	450,969	0.008	0.152	-0.063	0.003	0.067
$[-1, 20]$	455,147	0.015	0.192	-0.076	0.007	0.088

Table A4: Stage of the Regime and Performance of Sector Rotation Strategy

Exc. Ret.	CAPM	FF3	Carhart4	FF3+DUR	PS4	HXZ4	FF5
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Equal-Weighted							
First Half of Each Regime							
10.66**	10.70*	14.29***	13.25***	16.82***	15.13***	21.29***	17.46***
(2.09)	(1.88)	(3.34)	(3.28)	(4.01)	(3.69)	(4.47)	(4.56)
Second Half of Each Regime							
6.24**	6.86**	8.31***	4.63	7.32**	7.58**	4.61	6.54**
(2.09)	(2.26)	(2.70)	(1.62)	(2.07)	(2.56)	(1.39)	(2.06)
Panel B: Value-Weighted							
First Half of Each Regime							
8.62	7.35	12.10**	12.21**	16.47***	12.88***	22.38***	16.63***
(1.48)	(1.10)	(2.43)	(2.46)	(3.19)	(2.71)	(4.20)	(3.75)
Second Half of Each Regime							
6.75**	7.41**	8.42***	3.91	8.48**	7.32***	5.99*	7.08**
(2.29)	(2.47)	(2.83)	(1.36)	(2.40)	(2.67)	(1.89)	(2.22)