Exploiting Cyclical Economic Trends Using a Composite Indicator and a Sector Rotation Trading Strategy

April 14, 2021

Introduction

From the dot-com bubble of the early 2000s, to the 2008 housing recession and the 2020 COVID-19 pandemic, economic downturns have long been sources of significant pain for investors. During such times, many investors wish that they had a way to anticipate the oncome of a recession, allowing them to allocate their investments in preparation for the event. The objective of this study is to develop such a method of predicting a future recession, or at least recognizing when the economy is in the early stages of a downturn. In theory, this should allow investors to prepare and hopefully miss the worst of the losses during such periods.

Our motivation for conducting this study was twofold. First, we both experienced significant losses on our personal investments during the recession caused by the COVID-19 pandemic. Thus, we were especially concerned with developing a way to hopefully reduce our exposure to such adverse events in the future. Second, in discussing potential active investment strategies, we were both intrigued by the possibility of an active portfolio whose allocations are based on the current business cycle stage. If constructed correctly, such a portfolio may be expected to outperform the market during both economic expansion and recession. We were therefore motivated to attempt to develop this portfolio and test whether it truly achieves excess returns.

We develop a model which is a composite of widely recognized leading and coincident business cycle indicators. This model provides a signal of what stage of the business cycle the economy is currently in and makes this signal usable for investors. We then test the performance of different sectors during different stages, and develop a portfolio based in our findings. Finally, we test the ability of this portfolio to generate long-run excess risk-adjusted returns.

Our study contributes a new composite business cycle indicator based on past empirical evidence. In addition, our study proposes a new trading strategy based on this model, and empirically tests the effectiveness of the strategy. This model and strategy combination has not previously been discussed in the literature, and therefore represents a novel contribution.

In the next section of our paper, we will provide an overview of past literature surrounding this topic. This section will also discuss the empirical basis for our selection of business cycle indicators as well as our selection of methodology to develop our composite indicator. After this, we will outline the specific research questions and hypotheses we test in this study. We then discuss our selected methodology before showing the empirical results of our study. This section will provide results for both the effectiveness of our composite indicator in reflecting the business cycle and the excess returns generated by our proposed portfolio. We provide analysis of our results and discuss potential reasons for the observed portfolio performance. Finally, we outline some limitations of our study and provide some concluding remarks.

Literature Review

The topic of the business cycle has been extensively studied in past literature. Some previous studies have made a distinction between different types of cycles. Boehm and Summers (1999) distinguish between classical cycles and growth cycles. Classical cycles are fluctuations in the overall level of economic activity. Thus, a classical recession would involve a reduction in economic activity. Conversely, growth cycles are fluctuations in the rate of growth of economic activity. Thus, a growth recession may occur if the level of economic growth slows, even if it is still positive. A similar definition of these cycles is expanded upon in Marezak and Gómez (2016). For our study, we will focus on defining the classical cycle.

The decision to make use of a composite index is supported by Boehm and Summers (1999), who empirically show the improved effectiveness that can be achieved using a multivariate approach as opposed to a univariate one. The same paper also provides the basic definitions which we used for leading, coincident, and lagging indicators. Here, a coincident index is defined as comprising variables which are expected to contain information about the current state of the economy. A leading index is constructed from indicators which one would expect to contain information about the future economy, while a lagging index is constructed from indicators which tend to contain information about the past state of the economy (Boehm & Summers, 1999).

The decision to use fewer than 20 time series indicators is supported by Bujosa et al. (2019), who show that although the economy is vast and complex, it is possible to create a valuable indicator model using a small number of variables as opposed to hundreds. In this study, only nine time series are used, yet the model produced shows empirically significant power in reflecting the business cycle. Likewise, Creal et al. (2010), use a model consisting of eleven variables, yet they too are able to significantly model the business cycle.

Past literature was also significant in informing which types of time series are effective in modelling the business cycle, and whether those time series are leading, coincident, or lagging. Boehm and Summers (1999) suggest that variables such as industrial production, employment, and retail sales are coincident indicators. Hours worked, product price changes, and stock prices are some variables suggested to be leading. Lagging indicators include long-term unemployment, inventory levels, and interest rates. Similarly, Creal et al. (2010) suggest that industrial production, real retail sales, CPI inflation, and real nondurables consumption, among others, are valuable economic indicators and are useful in a model. The Conference Board (2001) also provide detailed empirical overviews of many potential economic indicators, which provided excellent evidence for our selection of variables.

Our methodology was also impacted by past methodologies used in the literature and their associated empirical results. Several articles have provided different methods of separating different components of data, which is vital for the construction of a consistent business cycle indicator. Mareznak and Gómez (2016) separate their data into a trend-cycle component and an irregular component. By contrast, Creal et al. (2010) separate their data into a trend component and a cycle component. Vraná (2014) also separates the data into trend and cycle components, although using a Hodrick-Prescott filter to do so. In their methodology, the OECD (2000) uses period-to-period changes to remove trends from their data, which is the approach we decided to use after examination of all possibilities. We used several other methods which are consistent with the methodology used by the OECD (2000), including their method of amplitude adjustment and composite creation.

Past literature also provides several different methods of defining which stage of the business cycle the economy is presently in, based on output from the associated models. Bujosa et al. (2019) suggests the following four stages and their associated conditions:

- Anticipation of a Recession
    - The first difference of a trend reaches its local maximum numerical value
- Confirmation of a Recession
    - The first difference becomes negative and remains so for at lead six months
- Anticipation of an Expansion
    - The first difference of a trend reaches its local minimum numerical value
- Confirmation of an Expansion
    - The first difference becomes positive and remains so for at least nine months

An alternative method is proposed by Dzikevičius and Vetrov (2012), who propose the following stages and their associated conditions:

- Downturn
    - The trend is decreasing but is above the mean
- Slowdown
    - The trend is decreasing and is below the mean
- Recovery
    - The trend is increasing but is below the mean
- Expansion

- The trend is increasing and is above the mean

Due to its intuitiveness and simplicity to implement, we chose to use the cycle stage definitions used by Dzikevičius and Vetrov (2012).

Research Questions & Hypotheses

The main focus of our study is to determine whether excess returns can be achieved by modeling the business cycle, then basing a portfolio on the results of the model. Thus, we first develop our model using the specified business cycle indicators and prescribed methodology. Our main objective in this area is to develop a model which effectively reflects the current and near future of the business cycle. This model should be able to provide signals on which stage of the business cycle the economy is presently in, which provides an objective basis for our sector weightings in our portfolio. The first hypothesis of our study is therefore:

H0: The developed business cycle composite indicator does not effectively reflect the current stage of the business cycle.

H1: The developed business cycle composite indicator does effectively reflect the current stage of the business cycle.

After developing our composite indicator, we then test the effectiveness of a trading strategy based upon the signals given by the indicator. We first employ a sample period, over which the performance of different market sectors is recorded in the various stages of the business cycle. Next, we develop a portfolio for each business cycle stage, based on which sectors performed best during that stage in the sample period. Finally, we use a test period to determine the performance of our portfolio, measuring alpha using the Fama-French 3-Factor Model. The second hypothesis of our study is therefore:

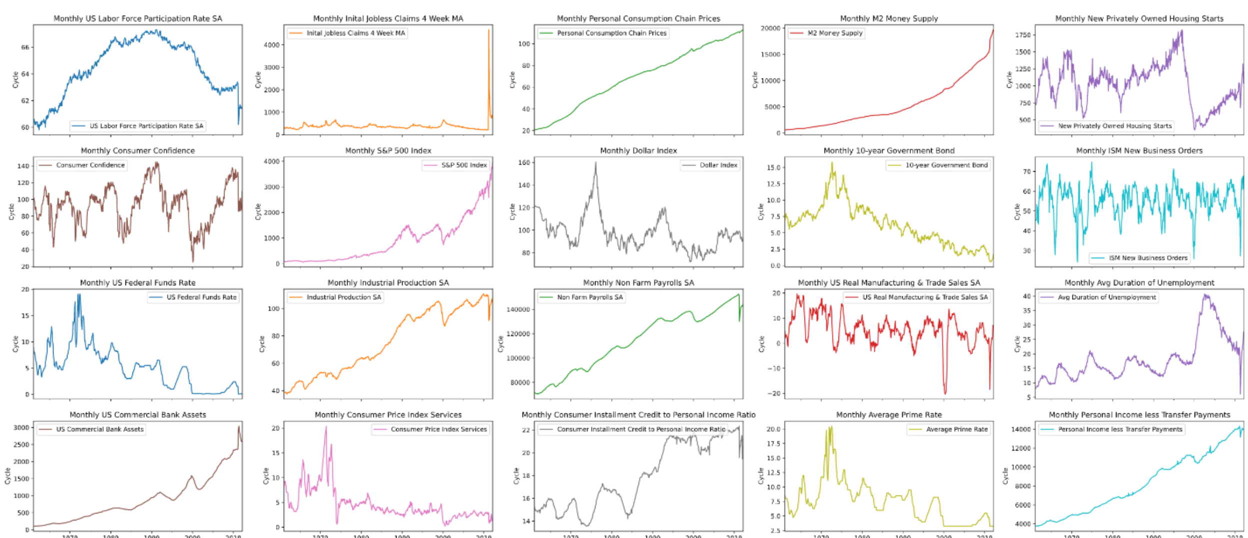
H0: The portfolio based on our composite business cycle indicator does not significantly outperform the S&P 500 Index.

H1: The portfolio based on our composite business cycle indicator does significantly outperform the S&P 500 Index.

Data and Methodology

Data

Using Bloomberg's Python API, we gathered over 20 economic indicators as defined by the Conference Board from 1970-2021 (The Conference Board, 2001). Furthermore, per the conference board's handbook, we focused on indicators that reported monthly and did not have a history of revisions. We believed that the indicators were chosen to represent a diverse selection of factors that significantly influence the business cycle. These factors include employment, manufacturing, consumption, access to credit, and investor sentiment.



After the business cycle was created, monthly returns from SPDR Sector Indexes and the S&P 500 Index were collected from the period 1994-2021. Data is then trained from the years 1994-2010 and then back tested from 2010-2021. Additionally, we gather factor data during this time from Fama and French.

Methodology

Business Cycle Construction

To construct the Leading and Coincident cycles, we use the Organization for Economic Co-operation and Development (OECD) methodology and the recommended series from the conference board (Brunet, 2014). We begin this process by transforming their corresponding indicators using a period-to-period change (PPC) to detrend the individual time series to ensure stationarity (Brunet, 2014).

$$S_t = \frac{X_t - X_{t-1}}{avg(X_t + X_{t-1})}$$

Where:
Xt: series of the economic indicator
St: PPC of economic series X
t: Time
We differ from the OECD methodology by winsorizing the top and bottom 10th percentiles to remove outliers' significant effects after this process. With the recent abnormal events such as the COVID-19 pandemic, economic indicators had significant outliers, which disrupted the cyclical decomposition of the time series (Darné & Charles, 2008). To smooth any additional volatility in the factors, we use a 12-month moving average for all indicators, excluding the average prime rate (3-month moving average).

We then adjust each series S amplitude to ensure that the cyclical component averages the detrended time series (Brunet, 2014). This allows for a more efficient calculation of lead-lag timings (OECD).

$$A_t = \frac{S_t}{mean(|S|)}$$

Where:

At: Amplitude adjusted series

St: PPC change of the economic indicator

|S|: Absolute mean value of series S

T: time

After the data has been cleaned, smoothed, and normalized, the data is aggregated into a corresponding leading and coincident indicators. This is done by taking the average amplitude adjusted value at time t for their corresponding series.

$$C_t = \frac{\sum_{i=0}^{N} a_{i,t}}{N}$$

Ct: Composite Index

Ai,t: Amplitude adjusted series I at time t

N: Number of indicators at time t going into the composite index

T: time

This resulted in two composite indexes of which we did not have an efficiently stationary long-term trend. We decided to use a Hodrick-Prescott filter to separate the cyclical component further away from the trend. HP filters are commonly used to analyze macroeconomic variables to smooth data while also analyzing the long-term trend (de Jong & Skarya, 2016). Using a smoothing factor of 129600 as suggested by Ravn and Uhlig (2002), we were able to ensure that the cyclical portion of our composite indexes. This allowed us to analyze the cyclical component of our time series and analyze short-term fluctuations in the business cycle.

$$f(\tau_t) = \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2,$$

Where:

yt: is the observed time series at time t

Tt: is the trend component at time t

λ: Is the smoothing parameter

To ensure that our cycles are usable for analysis, we must ensure that the data is stationary so that it can be used to analyze future expected values of the cycle (Mushtaq, 2011). We used the Augmented Dicky Fuller test for each cycle which is a test that determines if a series is stationary. Afterward, a granger causality test was performed to determine the leading indicator's optimal leading time. Creating a lead time for the leading indicator allows for a stronger signal as both indicators will have similar movements simultaneously. The cycles will then be combined into a business cycle using a 60/40 weighted average for the leading and coincident indicators, respectively.

With the business cycle now created, a signal to identify different business cycle periods must be generated. We use the methodology of Dzikevičius and Vetrov (2012), in which they define the business cycle using the cyclical components' current level and their momentum. We then use a 12-month average of our current combined cycle and a 3-month average in which we take the difference to identify the momentum. The four stages of the business cycle are then defined as followed:

Current Cycle Period	Index and Momentum
Expansion	Index > 100 and momentum > 0
Downturn	Index > 100 and momentum <0
Slowdown	Index < 100 and momentum < 0
Recovery	Index < 100 and momentum > 0

After the signals are generated, we can begin the construction of our sector rotation portfolio.

Portfolio Construction

Using our business cycle signal, we begin by replicating the empirical studies performed by Ung and Abburu (2019) and constructing the portfolios that they found outperformed. The portfolios are as follows:

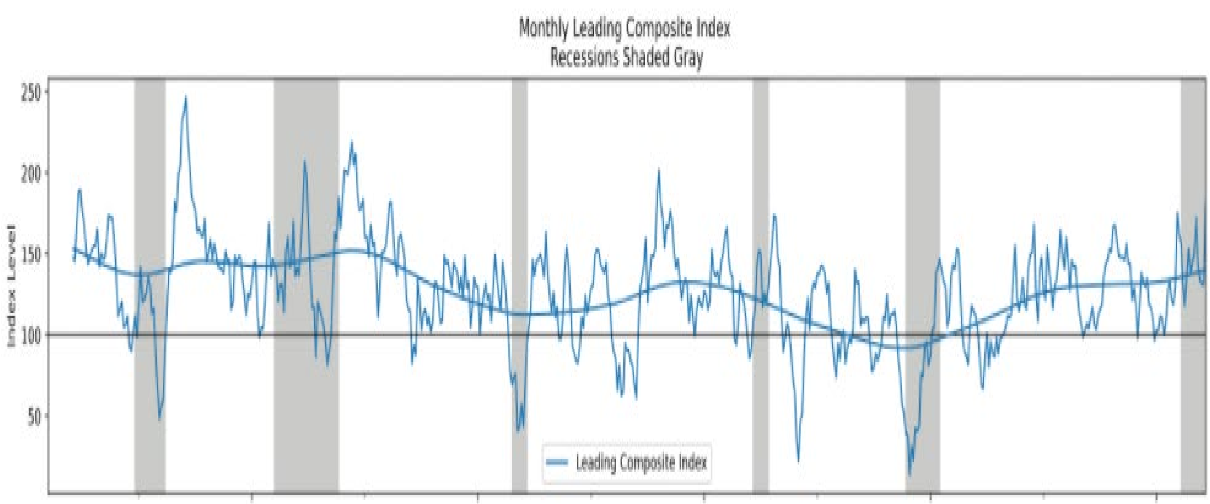
Current Cycle Period	Ung and Abburu portfolio tests
Expansion	Materials, Real Estate, Technology
Downturn	Consumer Discretionary, Industrials, Technology
Slowdown	Utilities, Real Estate
Recovery	Consumer Staples, Healthcare, Utilities

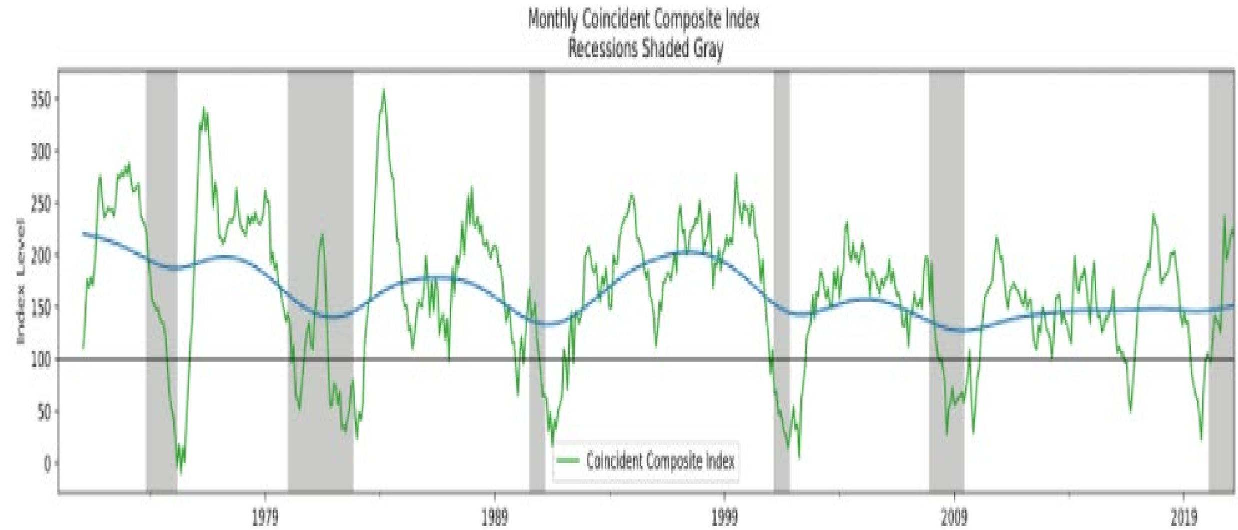
We then proceed to analyze their performance from the period 1992 to 2020 by identifying their cumulative returns. After this analysis, we then use our model to identify the outperforming sectors from 1992-2010 and create our portfolios that outperform during different sectors. We then use out of sample data for the years 2010-2020 to see how our portfolio compares to the S&P 500 Index. We will then analyze the benchmark and our portfolio by using standard risk metrics such as Sharpe ratios, skew, information ratios, etc. We will then use the 3 factor Fama French model to analyze the significant factors that affect our portfolio.

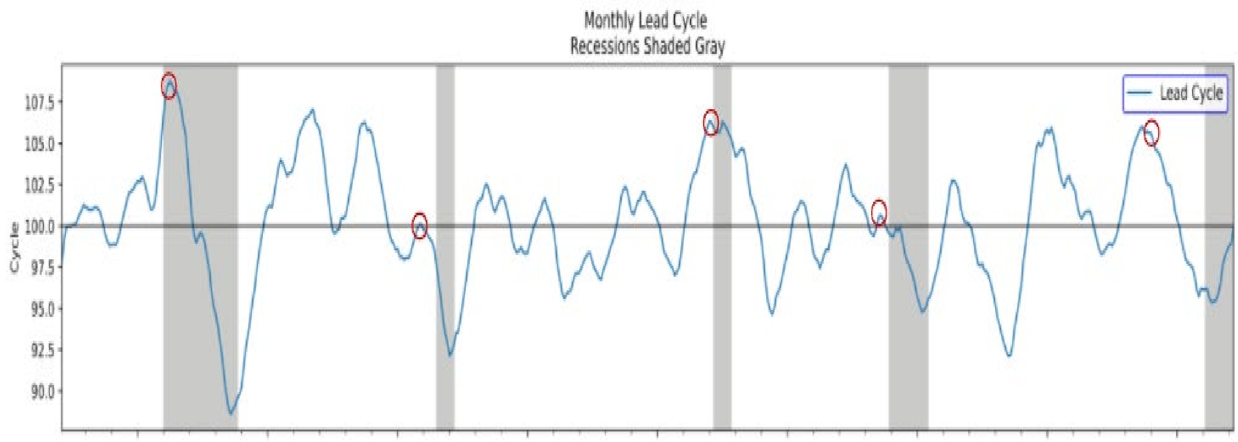
Results

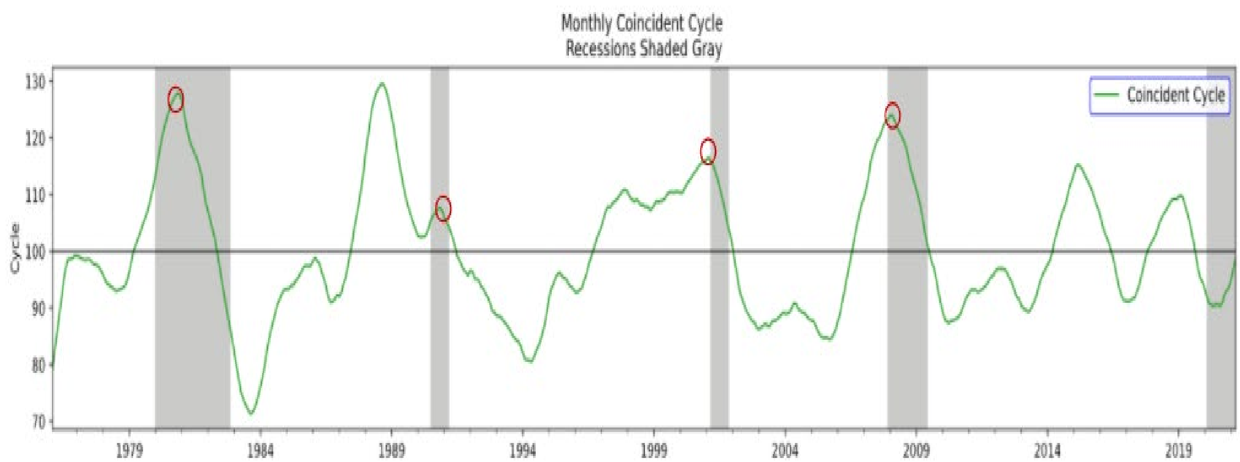
Using the methodology described above, we transformed our leading and coincident composite cycles by eliminating the HP filter trend component. We confirmed that our cycles either predicted economic events or coincided with them by plotting them against confirmed recession periods. We then analyzed how much our lead cycle led the coincident using the granger causality test. This test showed that a one-period lead time had the most robust F score at approximately 51.065. Using this information, we created our business cycle index using a 1-month lead time on our leading indicator. Since our leading indicator has predictive power, we weigh the cycle at 60% and the coincident cycle at 40%.

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=51.0635 , p=0.0000  , df_denom=598, df_num=1
ssr based chi2 test:   chi2=51.3197 , p=0.0000  , df=1
likelihood ratio test: chi2=49.2458 , p=0.0000  , df=1
parameter F test:         F=51.0635 , p=0.0000  , df_denom=598, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=23.0160 , p=0.0000  , df_denom=595, df_num=2
ssr based chi2 test:   chi2=46.4188 , p=0.0000  , df=2
likelihood ratio test: chi2=44.7108 , p=0.0000  , df=2
parameter F test:         F=23.0160 , p=0.0000  , df_denom=595, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=16.0816 , p=0.0000  , df_denom=592, df_num=3
ssr based chi2 test:   chi2=48.8152 , p=0.0000  , df=3
likelihood ratio test: chi2=46.9280 , p=0.0000  , df=3
parameter F test:         F=16.0816 , p=0.0000  , df_denom=592, df_num=3

Granger Causality
number of lags (no zero) 4
ssr based F test:         F=11.8924 , p=0.0000  , df_denom=589, df_num=4
ssr based chi2 test:   chi2=48.2963 , p=0.0000  , df=4
likelihood ratio test: chi2=46.4450 , p=0.0000  , df=4
parameter F test:         F=11.8924 , p=0.0000  , df_denom=589, df_num=4

Granger Causality
number of lags (no zero) 5
ssr based F test:         F=8.9031  , p=0.0000  , df_denom=586, df_num=5
ssr based chi2 test:   chi2=45.3511 , p=0.0000  , df=5
likelihood ratio test: chi2=43.7111 , p=0.0000  , df=5
parameter F test:         F=8.9031  , p=0.0000  , df_denom=586, df_num=5
```

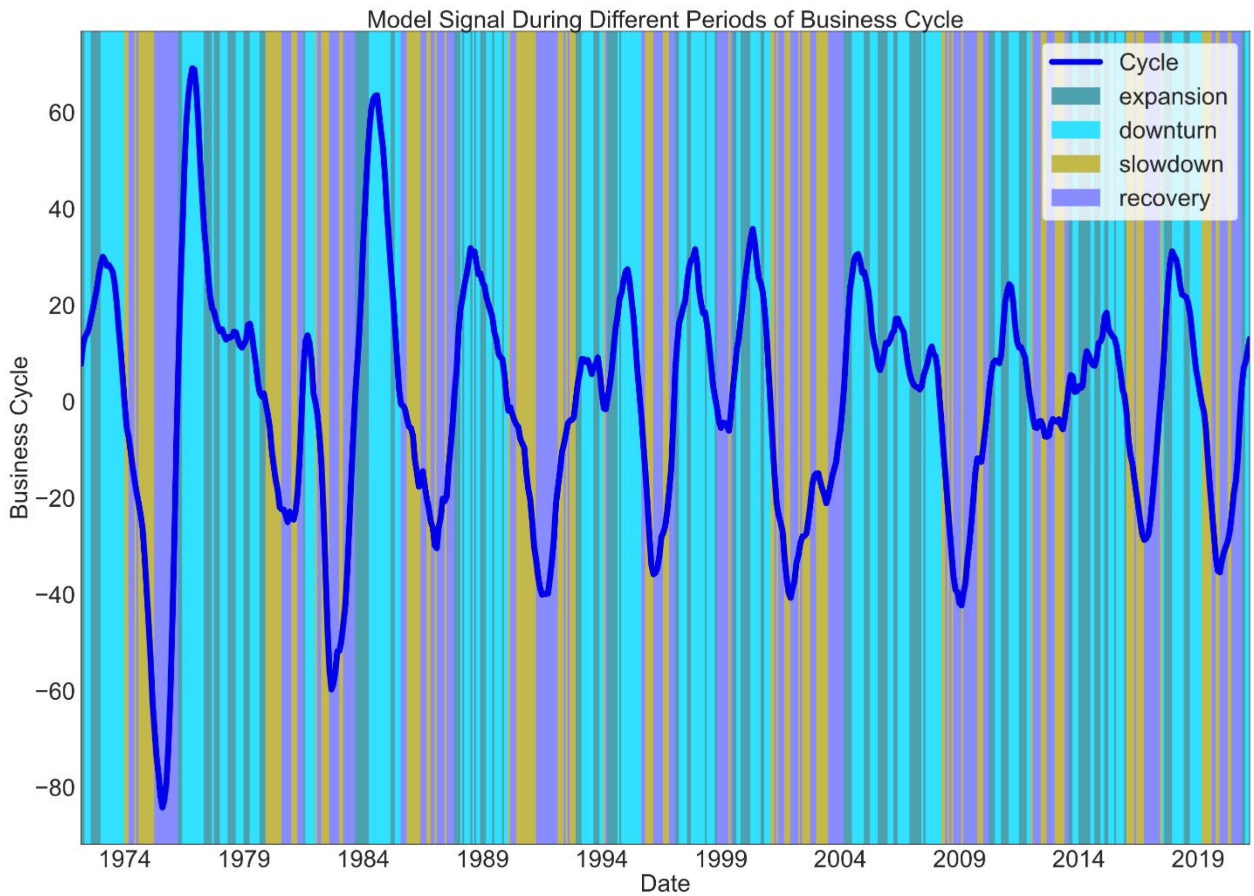



Monthly Coincident Composite Index
Recessions Shaded Gray
Index Level
350
300
250
200
150
100
50
0
Coincident Composite Index
1979
1989
1999
2009
2019

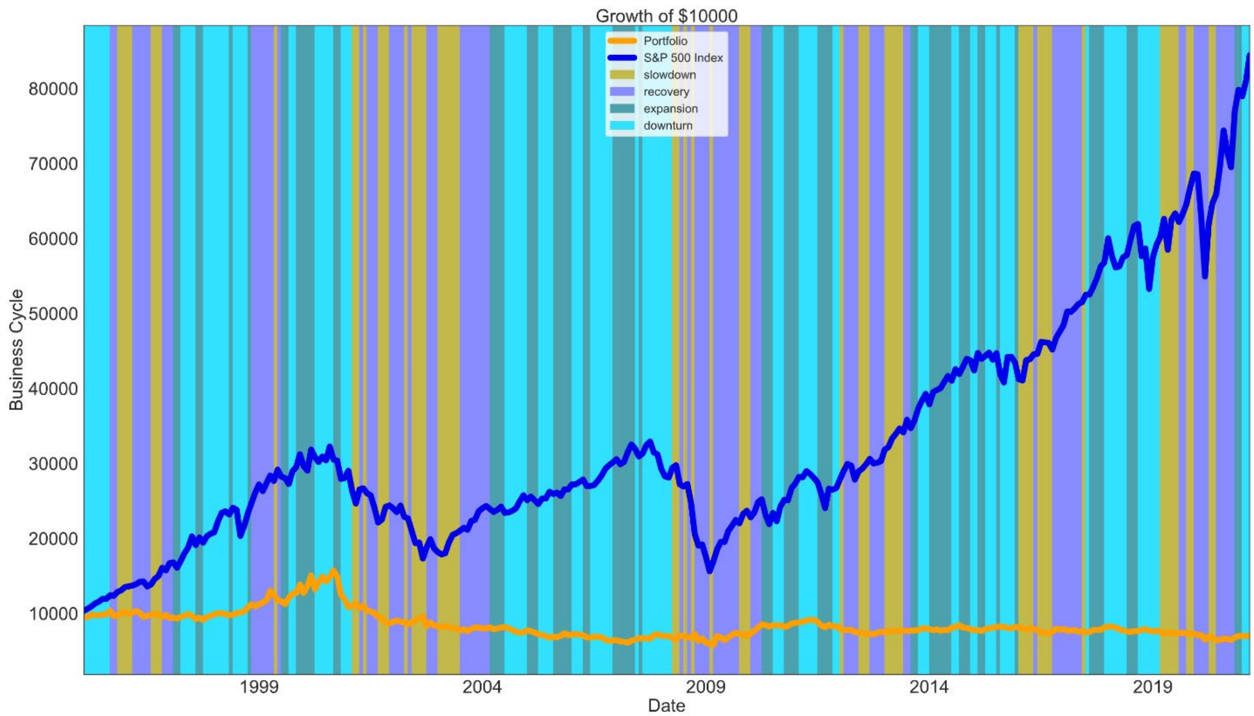

Monthly Lead Cycle
Recessions Shaded Gray
Cycle
107.5
105.0
102.5
100.0
97.5
95.0
92.5
90.0
Lead Cycle


Monthly Coincident Cycle
Recessions Shaded Gray
Cycle
130
120
110
100
90
80
70
Coincident Cycle
1979
1984
1989
1994
1999
2004
2009
2014
2019

With our cycle and signal created, we identified what periods of the business cycle our model suggested we were in and paired them with major events to see if it was accurate.



After confirming that our signal corresponded was accurate, we then backtested the portfolios from Ung and Abburu (2019) from the period 1992-2021. Naively following the empirical leads to the underperforming, the benchmark by over 700%. We suspect that the reason for this is the difference in models. Our model's slight differences could lead to significant timing differences, which could cause our model to differ from theirs. Additionally, their outperformers only included a maximum of 3 sectors which means that they miss out on much of the overall market gains.



After analyzing the results, we created our portfolios based on an in-sample analysis of sector performances during cycle periods. During 1992-2010, we found that the expansionary (signal = 1) periods often led to the outperformance of the Energy, Healthcare, Industrials, Information Technology, and Utility sectors. Our results have similar results in which Information Technology all outperform during this period. However, our results differ as Utilities, Healthcare, and Energy outperformed during this period while Real Estate underperformed. This could be due to the lower rate environments in which capital-intensive businesses such as Energy and Utilities outperform. Real estate may have underperformed due to the massive Real Estate sell in 2008, which significantly impacted housing prices during that period, and our sample size is only 18 years. Regarding health care outperformance, lower interest rates make it beneficial for companies to invest in R&D and develop new health care products.

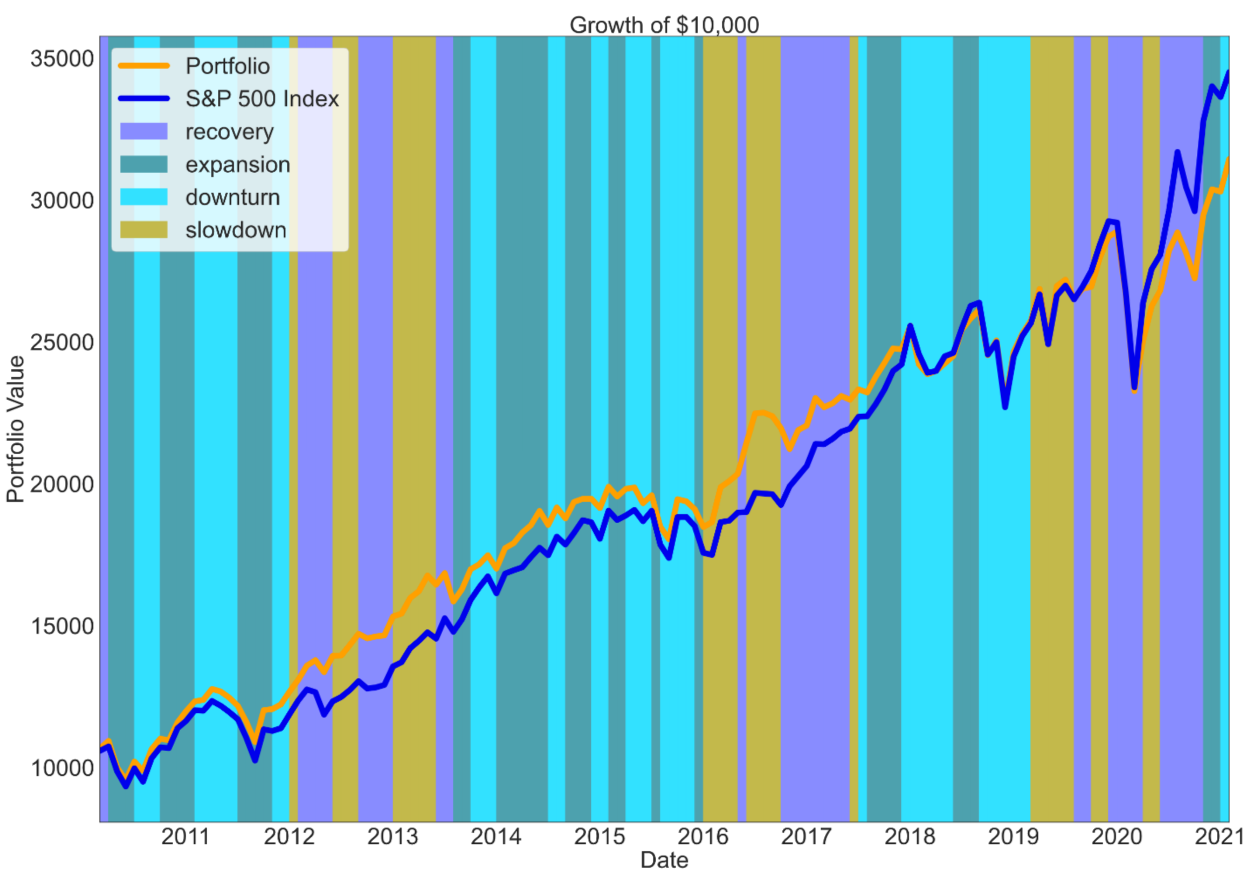
In the downturn periods (signal = 2), most sectors had annualized monthly returns of over 10% apart from Materials and Real Estate. This significantly differs from prior research as only consumer discretionary, Industrials, and Technology outperformed. An explanation for this occurrence could be that our business cycle is a leading indicator, meaning that sectors may take time to react to an actual downturn. In the slowdown period (signal = 3), Consumer Discretionary, Industrials, Materials, and Information Technology outperformed with returns over 10%, while Financials and Health care returned over 5%. In contrast, Utilities and Real Estate performed poorly with negative monthly returns. This differs from empirical research as utilities and real estate often outperform during slowdowns due to the declining growth rates in other asset classes (Ung and Abburu, 2019). In slowdown periods, real estate and consumer staples outperform with growth rates at approximately 10%, while communication services, consumer discretionary, industrials, information technology, and utilities underperformed. While consumer staples during this period typically outperform, healthcare and utilities differ in which prior research showed outperformance. We believe that healthcare and utilities may have underperformed due to rising interest rates, which deters R&D spending and capital expansions.

Signal	Communication Services	Consumer Staples	Consumer Discretionary	Energy	Financials	Health Care	Industrials	Materials	Real Estate	Information Technology	Utilities
1	-0.41%	0.99%	-2.23%	12.70%	-4.11%	15.70%	7.02%	2.72%	-0.58%	9.15%	5.17%
2	12.81%	17.04%	13.94%	20.30%	18.39%	16.24%	14.07%	9.53%	6.67%	22.18%	18.65%
3	3.77%	-2.20%	18.15%	2.61%	6.73%	9.61%	12.93%	15.16%	-2.03%	39.25%	-11.16%
4	-8.19%	9.48%	-2.10%	4.76%	0.97%	0.09%	-5.16%	0.61%	11.30%	-4.63%	-6.43%

With the information that our signal gathered, we can train our model to create portfolios with expected annualized monthly returns over 5% and backtest the portfolios from the period 2010-2020. Our portfolios are the following:

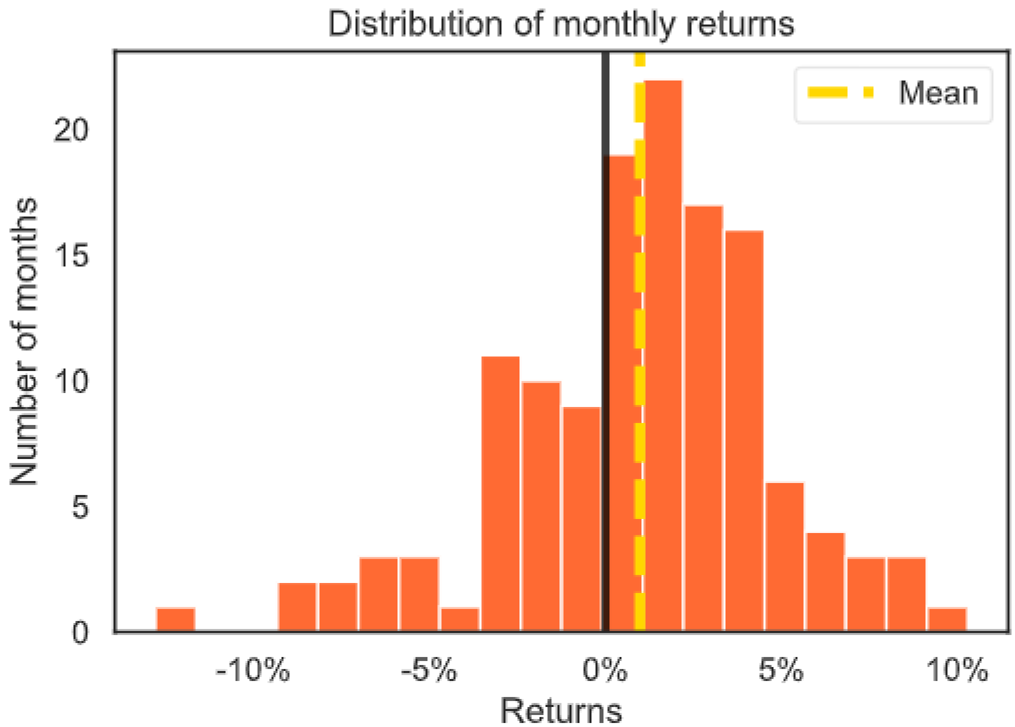
Cycle Period	Portfolio Allocation
Expansion	Energy, Health Care, Industrials, Information Technology, and Utilities
Downturn	All sectors
Slowdown	Consumer Discretionary, Financials, Health Care, Industrials, Materials, Information Technology
Recovery	Consumer Staples, Real Estate

With these portfolios created, we backtested using out-of-sample data and compare the results to the S&P 500.

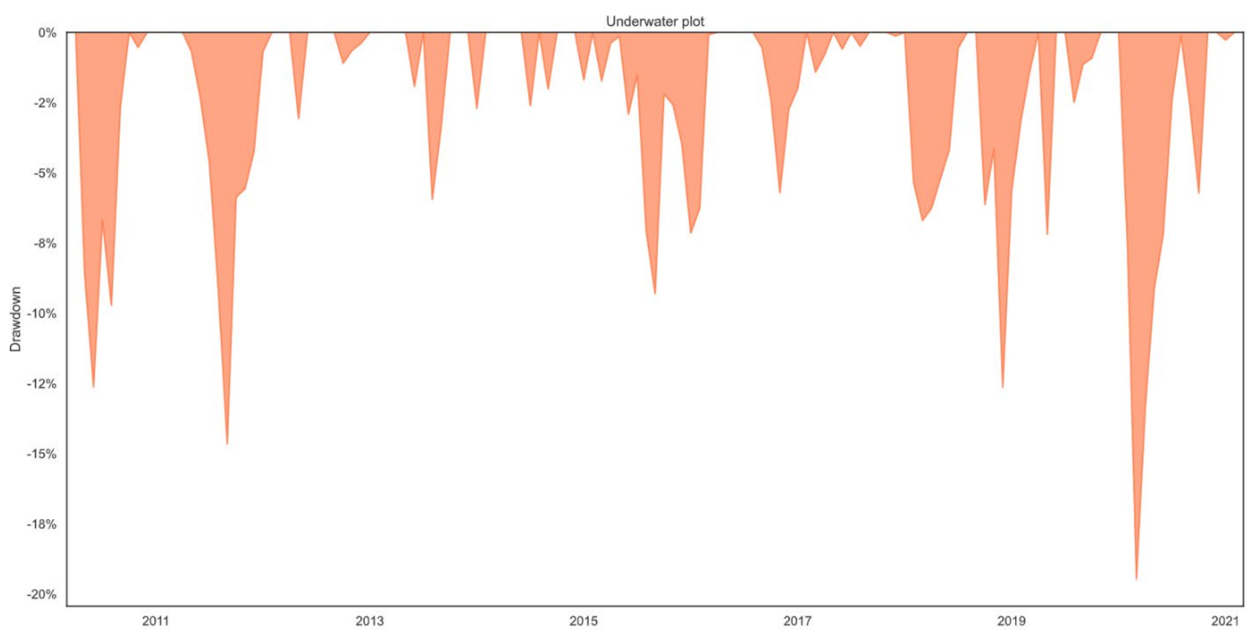


Portfolio Metrics (annualized)	Sector Rotation Strategy	Benchmark	Excess
Mean Return	11.91%	13%	-1.09%
Standard Deviation	13.05%	14%	-0.95%
Skew	-1.953	-1.137	-0.816
Kurtosis	4.079	3.216	0.863
Sortino	0.113	0.117	-0.004
Information Ratio	-0.0177	NA	NA
Value at risk (Monthly)	6.59%	7.06%	-0.47%
Sharpe Ratios	0.9127	0.928	-0.0153

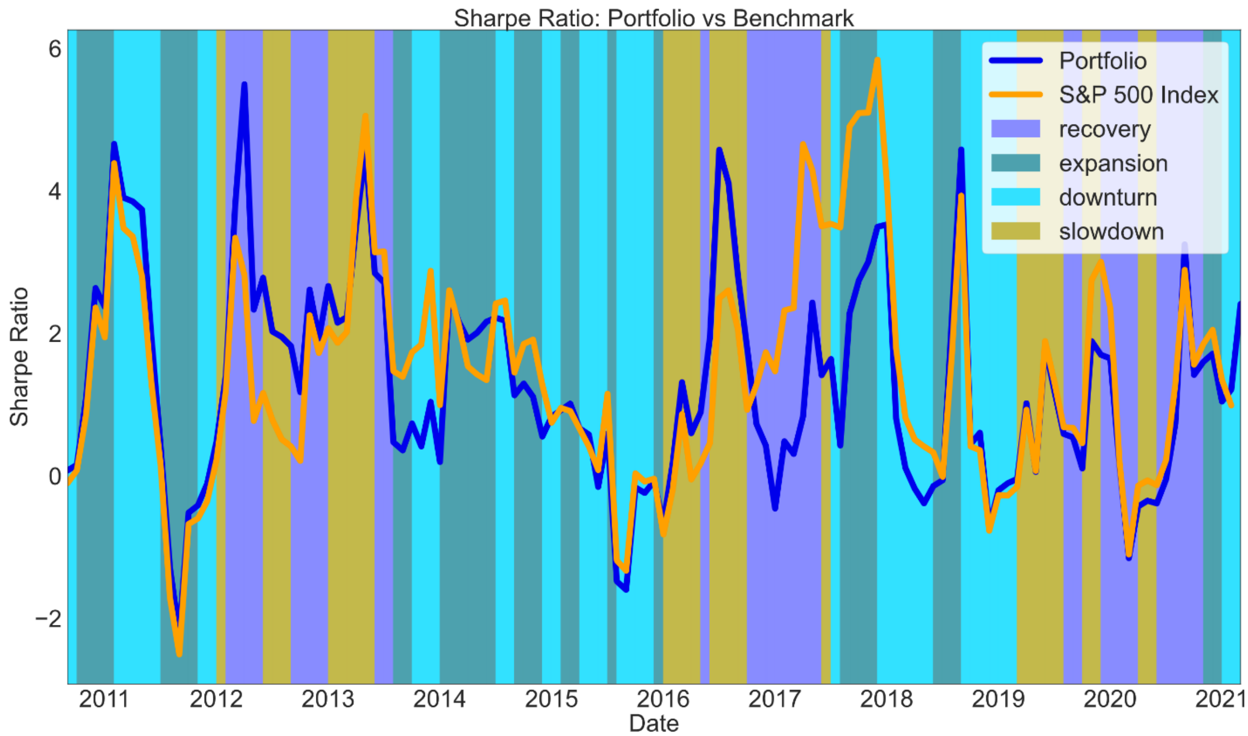
With regards to mean return, the sector rotation strategy underperforms by 1.09%. This could be due to timing differences in our rotation strategy, which causes the model to switch early due to our cycle's leading nature. Another explanation for the lower return could be our lower risk, as higher risk often leads to higher returns. Regarding our distribution of returns, we can see that our portfolio has a more significant negative skew. The negative skew suggests that our portfolio, on average, exhibits more frequent smaller gains than the benchmark. However, while our portfolio is more likely to have smaller gains, it also has a higher chance of significant tail risk, which implies our portfolio has large maximum drawdowns. Our portfolio is also leptokurtic in which the tail ends of the return distribution are "fatter." This means that our portfolio is prone to significant positive or negative returns.



Analyzing the portfolio's time underwater, we can see that our portfolio has infrequent large spikes in which the duration of the time underwater is less than a year. This shows that while our portfolio drawdowns are large, they are not long-lasting.



Our portfolio falls short regarding its Sharpe ratio, which means that an investment in the benchmark provides more risk-adjusted returns. However, this relationship is not constant over time as volatility and mean returns often change. Looking at the Sharpe ratio over time, the relationship of the benchmark and the portfolio's Sharpe ratio often change.

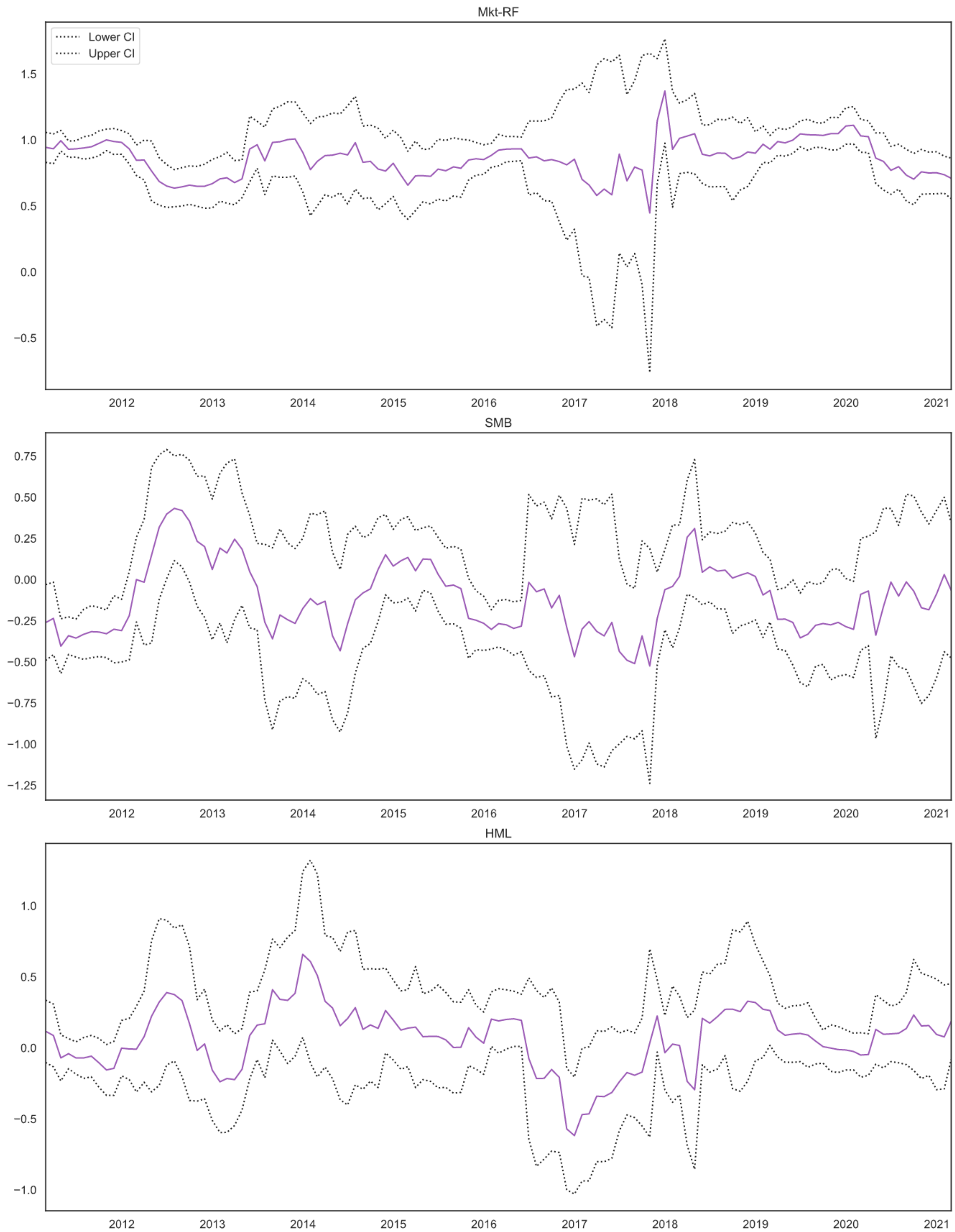


A portfolio's hit rate determines how often our portfolio beats the benchmark. In an expansion period, our portfolio beats the benchmark 37.1% of the time. This may be since each expansionary period is different, and our portfolio is only in a small subsection of the sectors. Furthermore, since each business cycle is different, the expansionary phases are most likely to change over time as different industries have different innovation rates. In a downturn period, our portfolio beats the benchmark 55% of the time. This may be due to the portfolio's weightings as we invested in the broad market with equal weights while the S&P 500 is market-cap-weighted. In the slowdown period, our portfolio beats the benchmark approximately 48% of the time. An explanation for this could be that returns during this period are primarily be due to market corrections in which investing in the S&P500 would diversify the portfolio more than investing our created portfolios. Lastly, our recovery portfolio beats the benchmark 56.67% of the time. This is primarily due to our portfolios focus on sectors with a history of outperformance during low-interest-rate environments. This is because interest rates are low as central banks lower their federal fund's rate to boost investment.

After identifying our portfolio performance, we identified the portfolio's factor contributions using the 3-factor Fama French Model. Our portfolio's alpha was statistically insignificant, showing that the market does not outperform or underperform the market. Our portfolio had a beta to the market risk premium of 0.8541, which means a 1 percent change in the market risk premium leads to our portfolio's excess return increasing by 0.8541%. The Small Minus Big factor's contribution to our portfolio has a statistically significant beta of -0.1455. This beta suggests that our portfolio relies on large-cap firms outperforming small-cap firms. Since the indexes from the SPDR are market cap-weighted, a reliance on large-cap stocks outperformance is expected. Lastly, the High Minus Low factor's contribution to our portfolio is statistically insignificant, suggesting that our portfolio doesn't rely on value or growth stocks for its return.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                port-rf   R-squared:                       0.875
Model:                            OLS   Adj. R-squared:                  0.872
Method:                 Least Squares   F-statistic:                     298.4
Date:                Wed, 14 Apr 2021   Prob (F-statistic):           1.42e-57
Time:                        15:15:29   Log-Likelihood:                 382.88
No. Observations:                 132   AIC:                            -757.8
Df Residuals:                     128   BIC:                            -746.2
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0009      0.001     -0.686      0.494      -0.003       0.002
Mkt-RF         0.8541      0.031     27.920      0.000       0.794       0.915
SMB           -0.1455      0.053     -2.754      0.007      -0.250      -0.041
HML            0.0485      0.045      1.078      0.283      -0.040       0.137
==============================================================================
Omnibus:                       45.280   Durbin-Watson:                   1.866
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              317.785
Skew:                          -0.924   Prob(JB):                     9.86e-70
Kurtosis:                      10.373   Cond. No.                         46.8
==============================================================================
```

Since these results are point estimates, we analyzed the factor-beta to see if there was a drastic change. The rolling beta's remained near a constant level across time which suggests that the factors are reliable.



Mkt-RF
Lower CI
Upper CI
1.5
1.0
0.5
0.0
−0.5
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
SMB
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00
-1.25
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
HML
1.0
0.5
0.0
−0.5
−1.0
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021

Limitations

Over the course of this study, we experienced several limitations which are important to note. First, before undertaking this study, we lacked experience regarding business cycle indicators or the construction of composite indexes. Thus, while we performed thorough research and examination of the topic, there is an increased potential for errors in our data or methodology.

Next, we experienced some limitations on the time period used for our measurements. In order to get a more accurate sense of the effectiveness of our composite index, as well as to better understand which sectors outperformed in which stages, we would have preferred to use data going back several decades, possibly as far back as 1945. However, data on individual sector performances only goes back to 1990, so what was the limit for the starting point of our data. As a result of this shorter measurement period, our results may not be as robust or statistically significant as we would have liked.

As a result of these limitations, there are some concerns that our model may not accurately reflect the stages of the business cycle. This is reflected by the fact that sector performances in our stages of the business cycle do not always match sector performances found in theory or past literature. In addition, overall market performance sometimes does not reflect our indicator. For example, sometimes the overall market continues to rise despite our indicator stating that the market is in a downturn.

Considerations

There are several considerations an opportunities for future research to expand on this study. Naturally, there are many different methodologies which could be used to create a composite business cycle indicator similar to the one in this study. Future research could focus on these alternative methodologies and attempt to determine their comparative effectiveness in creating a composite indicator. For example, machine learning could be used to analyze larger amounts of data and come up with more precise ways to measure which individual indicators are most effective, and how to measure exactly when a new stage of the business cycle begins.

Our study focuses only on equity returns. Future research could also incorporate returns from other asset classes, such as fixed income securities. This may result in a better understanding of how the business cycle affects the market for these alternative securities, and whether trading strategies can used with these securities to generate excess returns.

Our study uses a trading strategy of switching between different equity sectors depending on the stages of the business cycle. While this strategy did not produce many significant excess returns, future research could explore alternative strategies. For example, a study could examine a strategy which switches between equities and T-Bills or other risk-free securities during economic downturns. In theory, such a strategy should be effective at avoiding recessions, assuming that the trader can accurately measure the stages of the business cycle.

Finally, similar methodologies and strategies could be used to examine other types of economic cycles. The literature makes a distinction between the classical business cycle and the growth business cycle, with our study focusing on the classical cycle. Thus, there is a potential for research into the growth cycle, which would allow determination of whether a similar methodology and trading strategy can be used to generate excess returns based on the growth cycle instead of the classical cycle.

Conclusion

We created a composite business cycle indicator which was successful in reflecting the stages of the business cycle, as defined by the National Bureau Economic Research. When attempting to create trading strategies based on this model, we did not create any portfolios which saw significantly higher risk-adjusted returns compared to the benchmark market index. However, our portfolio did see a higher negative skew and a higher kurtosis, as well as a lower volatility compared to the market portfolio. This indicates a portfolio with risk characteristics which are favourable compared to the benchmark, which may be attractive to certain risk-averse investors.

Our study also provides some opportunities for future researchers in areas such as the use of machine learning or other methodologies to build more accurate composite indicators and more sophisticated trading strategies. Our paper could also be built upon to conduct studies involving other asset classes such fixed income securities. This may help to provide some insight into how the fixed securities market interacts with the business cycle.

This research is relevant to portfolio managers because it shows that it is possible to build a model which accurately reflects the business cycle, as well as providing some trading strategies which may be able to take advantage of such a model to generate excess returns. Managers may be able to alter or refine the strategies explored in this study in order to suit their clients' needs.

Bibliography

Boehm, E. A., & Summers, P. M. (1999). Analysing and Forecasting Business Cycles with the Aid of Economic Indicators. *International Journal of Management Reviews, 1*(3), 245-277. doi:10.1111/1468-2370.00015

Brunet, O. (2000). *Calculation of Composite Leading Indicators: A Comparison of Two Different Methods.* Paris, France: Orgainsation for Economic Co-operation and Development.

Bujosa, M., García-Ferrer, A., Juan, A., & Martín-Arroyo, A. (2020). Evaluating early warning and coincident indicators of business cycles using smooth trends. *Journal of Forecasting, 39*(1), 1-17. doi:10.1002/for.2601

Creal, D., Koopman, S. J., & Zivot, E. (2010). Extracting a Robust US Business Cycle Using a Time-Varying Multivariate Model-Based Bandpass Filter. *Journal of Applied Econometrics, 25*(4), 695-719. doi:10.1002/jae.1185

Darné, O., & Charles, A. (2008). The impact of outliers on transitory and permanent components in macroeconomic time series. *Economic Bulletin, 3*(60), 1-9. Retrieved from http://economicsbulletin.vanderbilt.edu/2008/volume3/EB-08C20064A.pdf

de Jong, R., & Skarya, N. (2016). THE ECONOMETRICS OF THE HODRICK-PRESCOTT FILTER. *The Review of Economics and Statistics, 98*(2), 310-317. Retrieved from https://watermark.silverchair.com/rest_a_00523.pdf?token=AQECAHi208BE49Ooan9kkhW_Ercy7Dm3ZL_9Cf3qfKAc485ysgAAApwwggKYBgkqhkiG9w0BBwagggKJMIIChQIBADCCAn4GCSqGSIb3DQEHATAeBglghkgBZQMEAS4wEQQMXfUPPlLl7SfVllOqAgEQgIICTw15_qZ9M00uSPwA2NT06RP9zbyUov6jivKrVfzRAT

Marczak, M., & Gómez, V. (2017). Monthly US business cycle indicators: a new multivariate approach based on a band-pass filter. *Empirical Economics, 52*(4), 1379-1408. doi:10.1007/s00181-016-1108-2

Mushtaq, R. (2011, August 17). Augmented Dickey Fuller Test. doi:http://dx.doi.org/10.2139/ssrn.1911068

OECD. (n.d.). *Composite Leading Indicators (CLI) Frequently Asked Questions (FAQs).* Retrieved from https://www.oecd.org/sdd/compositeleadingindicatorsclifrequentlyaskedquestionsfaqs.htm

The Conference Board. (2001). *Business Cycle Indicators Handbook.* The Conference Board.

Ung, D., & Abburu, S. (2019). *Asset Performance and the Business Cycle: A US Case Study.* State Street Global Advisors.

Vetrov, J., & Dzikevičius, A. (2012). Stock market Analysis through Business Cycle Approach. *Business: Theory and Practice, 13*(1), 36-42. doi:10.3846/btp.2012.04

Vraná, L. (2014). Business Cycle Analysis: Tracking Turning Points. *Applications of Mathematics and Statistics in Economics*, (pp. 277-283). Jerzmanowice, Poland.