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# INVESTMENT PORTFOLIO MANAGEMENT USING THE BUSINESS CYCLE APPROACH

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**Abstract.** A dissimilar performance characteristic displayed by asset classes over the economic business cycle has determined the purpose of this study - the integration of the business cycle approach into the construction of optimal investment portfolios. The paper combines business cycle, asset allocation and portfolio optimization theories by presenting a new model of the investment process and adding valuable information about the performance of asset classes in different phases of the business cycle. One of the best measures for the business cycle are leading indicators that can provide significant information on market expectations and future outlook; hence, every investor can improve his performance and risk management by adopting the results of this study. The use of the OECD Composite Leading Indicator as a business cycle measure assists in showing methods for constructing optimal portfolios and making investment decisions.
The conducted analysis uses 6 asset classes: US stocks, EAFE stocks, Bonds, Gold, Real estate and Commodities. Monthly data on the performed research covers the period from February 1976 to December 2011.

**Keywords:** portfolio optimization, asset classes, asset allocation, business cycle, OECD Composite Leading Indicators, investment strategies.

**JEL Classification:** G110, E320

# INVESTICIJŲ PORTFELIO VALDYMAS VERSLO CIKLO POŽIŪRIU

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**Santrauka.** Nevienodos turto klasių savybės ekonominio verslo ciklo metu lėmė šio tyrimo aktualumą. Pagrindinis tyrimo tikslas – verslo ciklo analizės metodų integracija į optimalių investicinių portfelių kūrimą. Šiame darbe sujungiamos verslo ciklo, turto alokacijos ir portfelio optimizavimo teorijos. Tokiu būdu sukuriamas naujas investavimo proceso modelis ir gaunama svarbios informacijos apie turto charakteristikas. Vienos veiksmingiausių verslo ciklo prognozavimo priemonių – aplenkiantys rodikliai, galintys suteikti svarbios informacijos apie rinkos lūkesčius, ateities perspektyvas. Tad tai yra puiki priemonė investuotojams, siekiantiems pagerinti rizikos valdymą ir pelningumą. Naudojant OECD aplenkiančius rodiklius kaip verslo ciklo matą, tyrime atskleidžiami optimalių verslo ciklo portfelių kūrimo metodai ir verslo ciklo koncepcijos taikymas investavimo sprendimams priimti.
Tyrimo metu buvo analizuotos šešios pagrindinės turto klasės: JAV akcijos, EAFE akcijos, obligacijos, auksas, nekilnojamasis turtas ir žaliavos. Analizuojant buvo naudojami mėnesiniai duomenys nuo 1976 m. vasario mėn. iki 2011 m. gruodžio mėn.

**Reikšminiai žodžiai:** portfelio optimizavimas, turto klasės, turto alokacija, verslo ciklai, EBPO aplenkiantys rodikliai, investavimo strategijos.

## Introduction

Nowadays, economic instability is commonly associated with business booms and recessions. We have become accustomed to speaking about these vicissitudes in economic fortune as the "business cycle". Business cycles are the results of cyclical changes in major macroeconomic forces of the economy. These forces are responsible for alterations in the "fundamentals" that affect asset prices. Thus, it is not surprising that research on asset valuation overwhelmingly finds a positive and statistically significant relationship between various assets and the state of the economy. Each asset has unique cash flow and risk characteristics during different phases of the business cycle.

Owen and Griffiths (2006) stated that business cycle analysis provided investors with a compass reading the whereabouts of the global markets. This is essential information they need before they start making decisions on the appropriate allocation of assets – equities, bonds, cash and other investments – within their portfolios. It also helps in determining geographic weighting. By setting stock selection within the context of cycle analysis, investors will know whether it is appropriate to chase momentum or pursue a more defensive strategy. To approach the business cycle, investors may choose from two ways one of which is to attempt to spot the turning points and shift asset allocation between various asset classes accordingly and the second is to ignore the business cycle completely and concentrate on picking good companies or identifying investment themes.

Many global asset classes in the 20th century produced spectacular gains in wealth for individuals who bought and held those assets for generational long holding periods. However, most of the common asset classes experienced painful drawdowns, while others complete elimination of wealth. Indeed, many investors can recall horrific 40–80% declines they faced in the aftermath of the global stock market crash only a few years ago. Thus, the main problem of this work is closely connected to the problems that face investors – the maximization of profit and the minimization of risk. The object of the thesis is the historical performance of asset classes and OECD Composite Leading Indicators. Accordingly, the main goal of this work is the integration of the business cycle approach to the construction of optimal investment portfolios.

The paper combines business cycle, asset allocation and portfolio optimization theories by presenting a new model of the investment process and adding valuable information about the performance of asset classes in different phases of the business cycle. It also demonstrates how to use the business cycle approach to investment decision making. 6 asset classes, including US stocks, EAFE stocks, bonds, gold, real estate and commodities have been applied in the conducted analysis.

Research methods used in this paper are the logical analysis and synthesis of scientific literature, the comparison and generalization method, statistical analysis and optimization taken on the grounds of the OECD Composite Leading Indicator approach.

## 1. Literature review

Academic literature contains much evidence that the expected returns and volatility of asset classes vary through time. Moreover, in high-volatility environments across the world, not only do equity returns perform poorly, but they also become more highly correlated.

In their study, Van Vliet and Blitz (2011) state that the risk and return properties of asset classes are highly dependent on the prevailing business cycle phase. Risk tends to go up in bad times, which is undesirable for a risk averse investor. Besides risk, the average return of many assets is also found to be highly dependent on the economic cycle phase. Most assets exhibit above-average returns during recessions and recoveries and below-average returns during expansions and peaks.

The results obtained by Nyberg (2012) also show that the strength of risk aversion appears to be significantly higher in the recession period compared with the expansion one. In addition, a conditional variance turns out to be higher during recession.

Guidolin and Timmermann (2007) found that optimal asset allocation varied significantly across the business cycle as weights on various asset classes strongly depend on the state the economy is perceived to get into.

The results used in the study by Sa-Aadu, Shilling and Tiwari (2006) confirm the value of portfolio diversification while providing interesting insights into the variation of gains in portfolio performance over the business cycle. A major finding of the paper is that commodities, precious metals and real estate appear to be powerful vehicles for hedging against adverse shocks to the opportunities for consumption growth. Not only do these asset classes offer significant gains in portfolio performance, but that gains vary directly with the standard deviation of consumption growth rate, which depends on the business cycle phase. This suggests that the optimal mean-variance tangency portfolio is heavily weighted in equities, REITs and government bonds in the bad state of the economy.

The paper by Seidl (2012) presents the differences of an out-of-sample analysis in performance and portfolio weights of the classical Markowitz approach and a business cycle dependent portfolio optimization. The business cycle model outperforms the classical Markowitz portfolio for both a risky and a risk averse investor.

Business cycle optimization also performs better under the aim for stable absolute performance. Business cycle strategic asset allocation leads to markedly better performance characteristics than through passive asset allocation (Van Vliet, Blitz 2011).

Grobys (2012) also confirms that when taking into account different business cycle phases, active strategies perform better than the passive ones.

Jensen and Mercer (2003) agree it is possible to improve the efficiency of the in-sample Markowitz portfolio by timing asset allocation shifts to turning points in the business cycle.

Siegel (1991) suggests that despite frequent dissociation between movements in the stock market and the business cycle, portfolios can be improved by switching between short-term fixed-income securities and equities before turning points in the economic cycle.

According to Dzikevičius and Zamžickas (2009), the most grounded explanation for recent economic downturns comes from Austrian business cycle theory confirming that, even during structural breaks, the business cycle theory can be used for explaining the major shifts in economy.

There are also numerous studies on examining the relationship between macroeconomic indicators and returns of asset classes. The debate has been spurred by Fama and French (1989) who have discovered business conditions to be responsible for a common variation in the expected return to both stocks and bonds. They detect dividend yield accurately forecasting bond returns and the default and term spread of bonds correctly predicting stock returns.

Xiufang (2010) in his research states that stock prices are not significant in explaining the real GDP, and vice versa. He also found that there was a bilateral causal relationship between inflation volatility and stock market volatility, confirming the existence of a feedback phenomenon between China's CPI and stock prices.

In US, Ibrahim (1999) established that macroeconomic forces influenced stock prices through their impact on the expected future cash flows. Chakravarty (2005) also stated that stock prices were highly sensitive to key macroeconomic indicators. Baranauskas (2010) confirms that various macroeconomic indicators directly influence stock markets. Akhtar (2012) points out that the business cycle phase has an impact on leverage ratios for companies and directly influences stock prices.

Pilinkus (2010) agrees that the determined direction of macroeconomic indicators compared with the stock market index enables to forecast tendencies towards variation in the macroeconomic environment of the country; their impact on the stock market also contributes to the formation of decisions made by investors.

Frankel and Saravelos (2010) accept international reserves and real exchange rate overvaluation as the top two indicators standing out as useful leading indicators of the current financial crisis.

Tunah (2010) examined causality relationships between variable pairs performing Granger causality test. According to the obtained results, there is bidirectional causality between stock returns and Dow Jones Industrial Average and between stock returns and Industrial Production Index. Moreover, unidirectional causality concerning the US Dollar, international crude oil prices, money supply, import and total credit volume to stock returns along with unidirectional causality regarding stock returns to Producer Price Index can be observed.

## 2. Data and methodology

The first step of the business cycle portfolio optimization process is the estimation of business cycle phases. Because of its popularity and data availability, OECD Composite Leading Indicators (CLI) as a business cycle measure are used. With reference to this approach focusing on turning points (peaks and troughs), four qualitatively different cyclical phases can be identified: expansion – CLI increasing and above 100, slowdown – CLI decreasing and above 100, downturn – CLI decreasing and below 100 and recovery – CLI increasing and below 100. Monthly data on research conducted from February 1976 to December 2011 were taken directly from the OECD web page (The Organization for Economic Co-operation and Development 2012).

The hypothesis that movements in economic indicators for CLI contains useful information concerning subsequent movements in different asset classes was back-tested using 6 assets: US stocks, EAFE stocks, bonds, gold, real estate and commodities. We also consider investment in the US dollar index. Table 1 shows data source and represents the index for each of the assets.

The first step of the business cycle portfolio optimization process is the estimation of the business cycle. Each time, the period is labelled according to the business cycle phase determined by CLI. Consequently, the monthly return of each asset can be assigned to a specific business cycle phase. It enables us to explore assets in different business cycle phases by various criteria such as return and risk. This brings to Step 2, where the inputs of assets should be set according to these labels. At this step, the expected returns, volatility and correlation estimates should be calculated for each business cycle phase, thus putting constrains on portfolio choice if needed. Step 3 constructs the utility function for each business cycle phase, which sets our goals for portfolio. Step 4 consists of portfolio optimization according to the specific business cycle phase. Thus, four different situations and four different portfolios that best satisfy our needs can be faced.

Mean-variance optimization applied to recoveries, expansions, slowdowns, downturns and full period allows unambiguous comparisons of asset allocations and portfolio risk alterations brought by cyclical shifts in economy.

Portfolio optimization was carried out using software package SMARTFOLIO 3 that can quickly and efficiently manage data, perform econometric and statistical analysis, generate forecasts, model simulations, etc.

**Table 1.** Data on asset classes

| Asset Class | Representing index | Source | Time period |
|---|---|---|---|
| US Stocks | S&P 500 index (S&P 500) | bloomberg.com | 02.1976–12.2011 (monthly) |
| EAFE stocks (Europe/Japan equity) | MSCI EAFE index (EAFE) | mscibarra.com | |
| Bonds | Barclays Capital U.S. Aggregate Bond Index (AGG) | bloomberg.com | |
| Gold | Gold | World gold council | |
| Real estate | FTSE NAREIT US Real Estate Index (REIT) | reit.com | |
| Commodities | S&P GSCITM Total Return Index (GSCI) | bloomberg.com | |
| US dollar | U.S. Dollar Index (DXY) | bloomberg.com | |

As a base case strategic asset allocation policy, equal asset weights in portfolio ("Balanced" strategy) are considered. Further, "Optimized" portfolio is provided. In this case, classical Markowitz optimization by maximizing portfolio return, subject to volatility to be less or equal to balanced portfolio volatility is employed. The input data are for a full period. "Balanced" and "Optimized" strategies are considered to be passive. Next, several dynamic asset allocation approaches based on our business cycle indicator (CLI) are examined. Each alternative is based on optimizing asset allocation for each of the four business cycle phases separately, where for each alternative a different set of restrictions is used:

– "Matching volatility". In each business cycle phase, return subject to volatility that does not exceed balanced portfolio volatility is maximized.
– "10% higher volatility". In each business cycle phase, return subject to volatility that does not exceed balanced portfolio volatility by 10% is maximized.
– "Optimizing volatility". In each business cycle phase, volatility subject to return constrain that must match the return of balanced portfolio is maximized.

Investment decision is made at the beginning of the next month after OECD CLI release.

## 3. Results

Preceding the comparisons of the Markowitz portfolio, it is informative to consider the return characteristics of six asset classes through all business cycle phases in isolation.

Table 2 shows that the separation of a full time period to OECD business cycle phases gives us interesting results. As expected, the return on equity, including US and EAFE stocks, real estate statistically better in recoveries, with the average monthly returns of 1.28%, 1.88% and 1.82% respectively. US stocks do significantly better than EAFE stocks for downturns, while reverse is true for EAFE during expansions. The following business cycle phase is best for commodities concerning a monthly return of 1.13%. Slowdowns are the worst for US and EAFE stocks with the average monthly returns of 0.72% and 0.29% accordingly, while this business cycle phase is the best for gold and commodities, with the average monthly returns of 1.34% and 1.27% respectively. The best business cycle phases for bonds – downturns is an average monthly return of 1.13% , whereas this period is the worst for commodities with a negative monthly return of 0.54%.

Not only returns vary over the business cycle, but also risk ratios significantly move. Specifically, standard deviations of asset classes rise for downturns.

**Table 2.** The performance of asset classes through the business cycle

| Business cycle phase | S&P 500 | EAFE | AGG | GOLD | REIT | GSCI | DXY |
|---|---|---|---|---|---|---|---|
| **Average monthly growth** | | | | | | | |
| Recovery | 1.28% | 1.88% | 0.53% | 0.41% | 1.82% | 0.96% | –0.12% |
| Expansion | 0.70% | 0.97% | 0.37% | 0.49% | 0.48% | 1.13% | –0.03% |
| Slowdown | 0.72% | 0.29% | 0.73% | 1.34% | 1.02% | 1.27% | 0.02% |
| Downturn | 1.19% | 0.69% | 1.13% | 0.61% | 0.97% | –0.54% | 0.01% |
| **Standard Deviation** | | | | | | | |
| Recovery | 4.01% | 4.36% | 1.55% | 4.74% | 3.53% | 4.48% | 2.43% |
| Expansion | 4.24% | 4.39% | 1.08% | 5.18% | 4.02% | 4.47% | 2.50% |
| Slowdown | 4.06% | 4.70% | 1.53% | 6.56% | 4.51% | 6.44% | 2.44% |
| Downturn | 5.32% | 6.37% | 2.16% | 5.75% | 6.78% | 6.40% | 3.14% |

Next, a comparison of passive asset allocation strategies (“Balanced” and “Optimized”) with the business cycle based asset allocation strategies defined in the methodology section is made. Table 3 displays optimal portfolio weights. We can also observe that business cycle based asset allocation weighs vary considerably through all business cycles phases. Our findings show that asset allocation for US stocks increases during expansions and downturns, EAFE stocks – during recoveries and expansions, bonds – during downturns, gold – during slowdowns, REIT – during recoveries and slowdowns, commodities – during expansions and slowdowns.

Table 4 indicates the return/risk characteristics of the examined asset allocation strategies. The table also shows that classic Markowitz optimization gives only slightly higher expected return compared to “Balanced” portfolio.

On other hand, business cycle based optimization provides much better return/risk characteristics. The historical simulation of “Matching volatility” strategy shows lower overall risk (ulcer index – 2.45%; standard deviation – 2.4%; max drawdown – 14.31%) and higher expected return (CAGR – 13.49%) compared to passive portfolio strategies (“Balanced”: CAGR – 10.03%; “Optimized” CAGR – 10.51%). Despite efforts for matching volatility to “Balanced” portfolio volatility, the overall volatility differs from “Balanced” portfolio due to different full period return/risk characteristics compared to each business cycle phase separately. Accordingly, considerable differences between “Balanced” portfolio max drawdown (–39.9%) and “Matching volatility” max drawdown (– 14.31%) can be noticed.

By increasing volatility constraint on each business cycle phase by 10%, “10% higher volatility” strategy for less risk averse investors is created. This strategy also has better return/risk characteristics compared to passive strategies: ulcer index – 2.78%, standard deviation – 2.6%; max drawdown – 15.25%; CAGR – 14.07%. Compared to “Matching volatility” strategy, the full period volatility of “10% higher volatility” strategy is 8.2% higher (relative measurement), while CAGR is higher only by 4.3%. This indicates that a further increase in the unit of risk provides a relatively smaller increase in return.

The last business cycle based strategy “Optimizing volatility” is designed for showing limits on minimizing volatility. In this case, similar return ratios (CAGR – 10.33%) compared to “Balanced” portfolio but with much lower risk: ulcer index – 1.58%, standard deviation – 1.63%, max drawdown – 9.8% can be observed.

**Table 3.** Weights of asset allocation strategies

| Business cycle phase | Balanced | | | | | | |
|---|---|---|---|---|---|---|---|
| | **S&P 500** | **EAFE** | **AGG** | **Gold** | **REIT** | **GSCI** | **DXY** |
| Full period | 16.67% | 16.67% | 16.67% | 16.67% | 16.67% | 16.67% | - |
| **Optimized** | | | | | | | |
| | S&P 500 | EAFE | AGG | Gold | REIT | GSCI | DXY |
| Full period | 19.74% | 4.70% | 30.96% | 6.76% | 37.19% | 0.65% | - |
| **Matching volatility** | | | | | | | |
| | **S&P 500** | **EAFE** | **AGG** | **Gold** | **REIT** | **GSCI** | **DXY** |
| Recovery | – | 21.00% | 31.00% | – | 46.00% | 2.00% | – |
| Expansion | 4.40% | 24.10% | 34.50% | – | – | 37.00% | – |
| Slowdown | – | – | 26.30% | 22.50% | 28.40% | 22.80% | – |
| Downturn | 12.45% | – | 87.55% | – | – | – | – |
| **10% higher volatility** | | | | | | | |
| | **S&P 500** | **EAFE** | **AGG** | **Gold** | **REIT** | **GSCI** | **DXY** |
| Recovery | – | 25.00% | 23.50% | – | 51.50% | – | – |
| Expansion | 5.00% | 26.50% | 27.60% | – | – | 40.90% | – |
| Slowdown | – | – | 18.38% | 24.78% | 31.75% | 25.10% | – |
| Downturn | 12.45% | – | 87.55% | – | – | – | – |
| **Optimizing volatility** | | | | | | | |
| | **S&P 500** | **EAFE** | **AGG** | **Gold** | **REIT** | **GSCI** | **DXY** |
| Recovery | – | 11.50% | 47.70% | 2.30% | 33.80% | 4.70% | – |
| Expansion | 2.60% | 17.20% | 54.00% | – | – | 26.20% | – |
| Slowdown | – | – | 65.76% | 11.60% | 10.40% | 12.25% | – |
| Downturn | 2.37% | – | 57.09% | – | – | – | 40.54% |

**Table 4.** Historical performance of asset allocation strategies

| | 03.1976–12.2011 | Balanced | Optimized | Matching volatility | 10% higher volatility | Optimizing volatility |
|---|---|---|---|---|---|---|
| Profit | Growth per period | 2970% | 3496% | 9204% | 11076% | 3287% |
| | Mean monthly return | 0.84% | 0.88% | 1.09% | 1.14% | 0.84% |
| | CAGR | 10.03% | 10.51% | 13.49% | 14.07% | 10.33% |
| Risk | Ulcer index | 6.59% | 5.50% | 2.45% | 2.78% | 1.58% |
| | Standard deviation (monthly) | 2.79% | 2.80% | 2.40% | 2.60% | 1.63% |
| | Volatility | 9.78% | 9.78% | 8.28% | 8.96% | 5.64% |
| | Max drawdown | –39.90% | –38.77% | –14.31% | –15.25% | –9.80% |
| | Average drawdown | –3.00% | –2.27% | –1.24% | –1.44% | –0.81% |
| Ratio | CAGR/Ulcer index | 1.52 | 1.91 | 5.51 | 5.07 | 6.52 |
| | CAGR/Standard deviation | 3.59 | 3.75 | 5.61 | 5.41 | 6.32 |
| | CAGR/Volatility | 1.03 | 1.07 | 1.63 | 1.57 | 1.83 |
| | CAGR/Max drawdown | 0.25 | 0.27 | 0.94 | 0.92 | 1.05 |
| | CAGR/Average drawdown | 3.34 | 4.62 | 10.87 | 9.77 | 12.83 |

Figure 1 shows the return/risk characteristics of asset allocation strategies in each business cycle phase. Mean/standard deviation ratio has been chosen to represent return and risk. In each business cycle phase, cyclical asset allocation strategies perform better than the passive ("Balanced" and "Optimized") ones. Business cycle based asset allocation strategies perform considerably better than passive strategies for downturns, whereas for other business cycle phases, mean/standard deviation ratios are only slightly higher.

For the full period, all business cycle based portfolios showed considerably better return/risk characteristics compared to passive portfolios mostly due to considerably better return/risk characteristics of downturns. An investor could realize a compounded annual return of 10.33–14.07% with a standard deviation of 1.63–2.6% and max drawdown of 9.8–15.25% from following our business cycle strategies versus 10.03% return with a standard deviation of 2.79% and max drawdown of 39.9% from the buy-and-hold "Balanced" strategy. These results can be treated as economically significant.

An investor can readily replicate our business cycle based strategies by easily switching between appropriate ETF's.

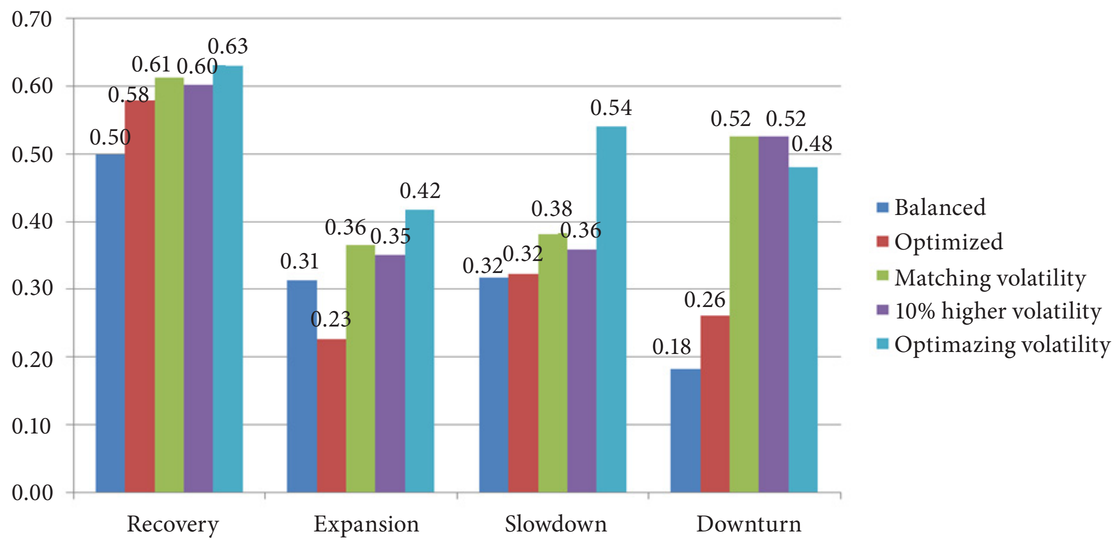


**Fig. 1.** Mean/standard deviation ratio of asset allocation strategies through business cycle phases

## Conclusions

The paper shows differences in performance and portfolio weights of the classical Markowitz approach, equal weighting and business cycle based portfolio optimization. In particular, the following points could be considered. First, empirical findings show that return and risk properties of asset classes vary considerably across business cycle phases and the risk of asset classes tends to increase during downturns. When using this insight, we suggest a practical investment framework for dynamic asset allocation across the business cycle. Second, optimization across the business cycle with different risk assumptions shows a varied pattern of optimal cyclically induced asset proportion alterations. Third, the historical simulation of cyclical asset allocation strategies shows better performance characteristics than passive strategies by means of all return/risk measures. Passive portfolio return and risk structure change considerably along with the phases of the business cycle. This fact reveals that in the absence of cyclical rebalancing, investment benefits enjoyed during recoveries, expansions and slowdowns are substantially diluted during downturns. Passive management can result in a less than optimal return/risk profile over a complete business cycle.

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