Business Cycle Based Portfolio Optimisation[*]

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Abstract

This study examines if dissimilarities in asset class behaviour over the business cycle can be used to add value to portfolio optimisation. We perform an in-sample analysis and observe three phenomena that can be used to enhance portfolio performance over the business cycle. First, we find that different asset classes perform best in terms of risk-adjusted returns during each business cycle stage. Second, we find that the optimal compensation for risk differs per business cycle stage. Third, we find that leading the movement of business cycle improves portfolio performance. We propose two models that we find to successfully enhance portfolio performance by adjusting for these phenomena in an out-of-sample analysis; a model that switches its asset allocation over business cycle stages, and a Black-Litterman extended to also adjust asset allocations to business cycle stages. These models enhance out-of-sample performance over portfolios with fixed allocations by 31-57% in terms of Sharpe ratios, in a mean-variance framework.

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Chapter 1
Introduction

Asset classes are known to exhibit time-variation in their risk and return characteristics over the business cycle. Business cycles are the fluctuations in the aggregate economic activity that drive fundamentals that affect asset prices. A well-known phenomenon is the increase in returns of equity assets when the economic activity increases while those of debt assets increase when economic activity decreases. Although this is established in literature, risk and returns characteristics are commonly assumed constant in portfolio optimisation, resulting in constant asset allocations over time. As a result, portfolios exhibit time-varying risk and return characteristics as well. This leaves room to improve portfolio performance over the business cycle by adjusting for the time-varying characteristics of asset classes.

This study focuses on the combination of the business cycle and portfolio optimisation in the field of asset allocation. The purpose of this study is to quantify the potential to enhance portfolio performance by adapting a portfolio's asset allocation for the business cycle. We first determine the potential in sample, using data available ex-post, and then expand those finding out-of-sample, using only data available ex-ante. We use mean-variance optimisation as pioneered by Markowitz (1952) to optimise portfolios over a time period spanning from 1973 to 2015.

We add to the existing literature on asset classes, by providing an extensive analysis of asset class behaviour in general, and by comparing their performance over each of the four stages of the business cycle. Previous research has often focussed on asset classes over the business cycle in isolation, or it has looked at the whole universe of asset classes without regard for the cyclical impact of the business cycle.

We provide new insights on the in-sample potential of business cycle based asset allocation by means of ex-post portfolio optimisation, while accounting for the four stages of the business cycle. This adds to the two stage approaches on both the business cycle, and the monetary cycle of Brocato and Steed (1998) and Jensen and Mercer (2003). A related study by Siegel (1991) found additional value by adapting asset allocations before the business cycle goes into the next stage. We add by expanding his findings on a two stage business cycle to determining the optimal lead time on all four stages.

Finally, we investigate the out-of-sample potential of business cycle based asset allocation and portfolio optimisation. We compare this with the in-sample analysis to assess how much of the potential of business cycle based portfolio optimisation can be captured using an index of leading indicators. To perform this out-of-sample analysis, we use the Organisation of Economic Co-operation and Development's System of Composite Leading Indicators (OECD CLI). This index tries to predict turning points in economic output ex-ante. First, we perform this analysis through a model that switches between allocations based on turning points in the business cycles comparable to previous research (Blitz & Van Vliet, 2009; Dzikevičius & Vetrov, 2012). Thereafter, we implement an extended Black-Litterman model in an out-of-sample analysis to enhance portfolio performance. We also add to literature by using a mean-variance utility function that incorporates risk aversion to optimise portfolios over the business cycle, whereas previous research often used Sharpe ratio optimisations.

Main research question

This study is divided in three different parts. First, this study analyses and compares asset class behaviour over the business cycle in terms of excess returns, volatilities, correlations and risk-adjusted returns. Second, this study investigates how the business cycle can be used to improve asset allocation in a mean-variance optimisation framework in sample. Third, this study uses the OECD's System of Composite Leading Indicators to assess the potential of using business cycle forecasts to enhance portfolio optimisation out of sample. These actions lead to the answers to our research question:

How does asset class behaviour change over the course of the business cycle, and can this add value to portfolio optimisation through asset allocation?

The remainder of this study is structured as follows. Chapter 2 discusses the theoretical background of the concepts central in this study, and reviews previous literature in this field. Chapter 3 lists our data sources and alterations made to the data. In Chapter 4 we provide an extensive comparison of asset class behaviour over the business cycle. Chapter 5 concludes on the potential to enhance portfolio performance in sample, based on the findings of Chapter 4. In chapter 6 we assess whether the in-sample findings of Chapter 5 can also be achieved out of sample. Chapter 7 summarises and concludes this study.

Chapter 2

Theoretical framework

In this chapter, the theoretical background of this thesis is provided. We start by introducing the workings and measurement of the business cycle. In addition, we discuss a theoretical investor, who is central in this study, and his/her goals and constraints. Furthermore, we introduce the universe of asset classes that is available to the investor. We discuss each asset class reviewing literature on its characteristics, performance, relationship with the business cycle and value for asset allocation. Finally, we review existing literature on business cycle based portfolio optimisation.

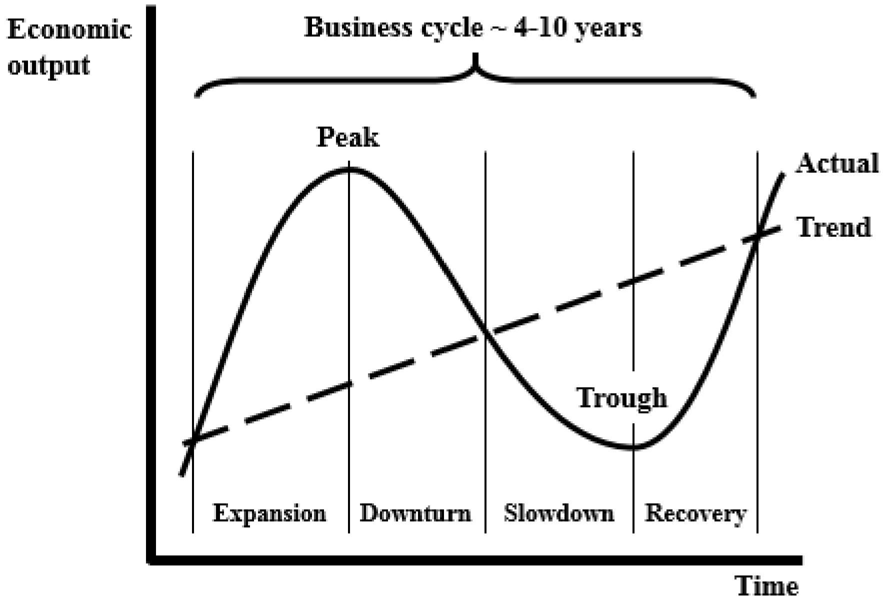
2.1 The business cycle

The business cycle articulates the evolution of the economy through time. The standard definition of the business cycle was established by Burns and Mitchell (1946): “Business cycles are a type of fluctuation found in the aggregate economic activity...” The business cycle is important for all participants of the economy, not only because of the fluctuations in economic activity, but there is a strong relation between the business cycle and monetary policy, credit availability, and profit margins (Hamilton & Longis, 2015).

The business cycle is composed of four stages: expansion, downturn, slowdown and recovery. These stages succeed each other in the provided order, and the cycle is repeated again at the end, as illustrated in Figure 2.1. The business cycle phases are defined as follows:

- Expansion: growth is above trend and increasing
- Downturn: growth is above trend and decreasing
- Slowdown: growth is below trend and decreasing
- Recovery: growth is below trend and increasing

Figure 2.1
The business cycle

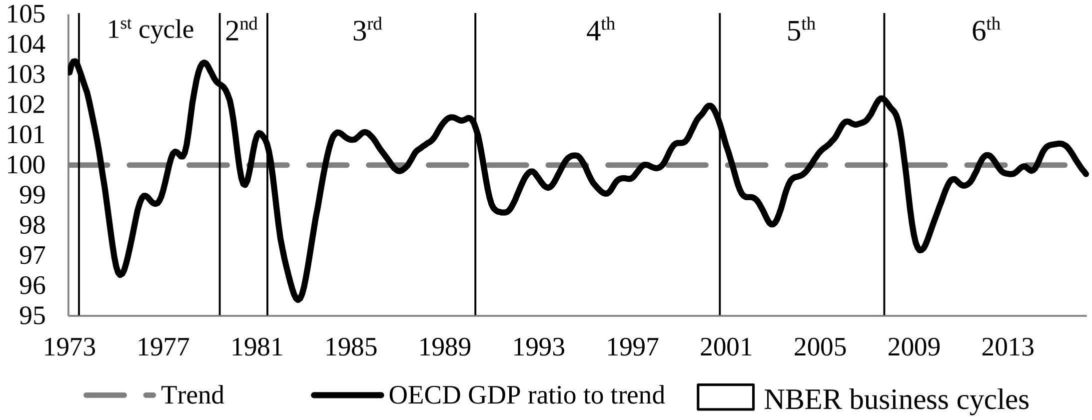


2.1.1 Business cycle measurement

In the United States, the National Bureau of Economic Research (NBER) is the official institution that monitors the business cycle and determines the dates of peaks and troughs. The NBER business cycle, however, is not usable in this study for two reasons. First, NBER peaks and troughs are determined long after they have happened, sometimes as long as 18 months later. This means that the data are not usable for decision making. Second, NBER only derives the peaks and troughs for the overall business cycle, and not the starting dates for each of the four individual stages. For this study, we assess all four stages of the business cycle.

For the in-sample (ex-post) analysis we use OECD GDP data. The OECD calculates the data on a monthly basis, and this is much more beneficial compared to the official quarterly GDP data compiled by the Bureau of Economic Analysis. Another benefit of OECD GDP data is that the OECD also analyses the GDP trend. The data is published after de-trending and represented as a ratio to the trend. This allows us to directly derive business cycle stages from the data without further changes to the data. We, therefore, use the GDP ratio to trend data from the OECD to assess historic business cycle stages. The OECD GDP ratio to trend and six NBER business cycles that fall in our analysis are presented in Figure 2.2. The NBER cycles are measured as a period between two peaks.

Figure 2.2
The OECD GDP ratio to trend and NBER business cycle for the U.S., Trend = 100



Sources: OECD (2016) and NBER (2016)

2.1.2 Business cycle prediction

We perform an out-of-sample (ex-ante) analysis after the in-sample (ex-post) analysis to assess the use of the business cycle for investors. The business cycle has to be predicted to be able to use it for investment decision making. The OECD GDP data are published with a delay of three months; they can, therefore, only be used for ex-post analysis. Dzikevičius and Vetrov (2012), who have researched the performance of specific asset classes through the business cycle, use an index constructed from leading economic indicators to assess the stages of the business cycle out-of-sample. Indices such as this combine many different leading indicators into one predictive measurement of the business cycle. We use an index of leading indicators in this study as well.

The OECD system of Composite Leading Indicators (OECD CLI) and the Conference Board Leading Economic Index are amongst the most well documented indices of leading indicators for the U.S. In this study we use the OECD CLI to assess the business cycle in a similar way as Dzikevičius and Vetrov (2012) have done. The major advantages of the OECD CLI over other indices are the free availability of data, extensive description of the methodology, ease of use, specified lead time on the economy of six to nine months and long historic time series since 1955 (OECD 2016).

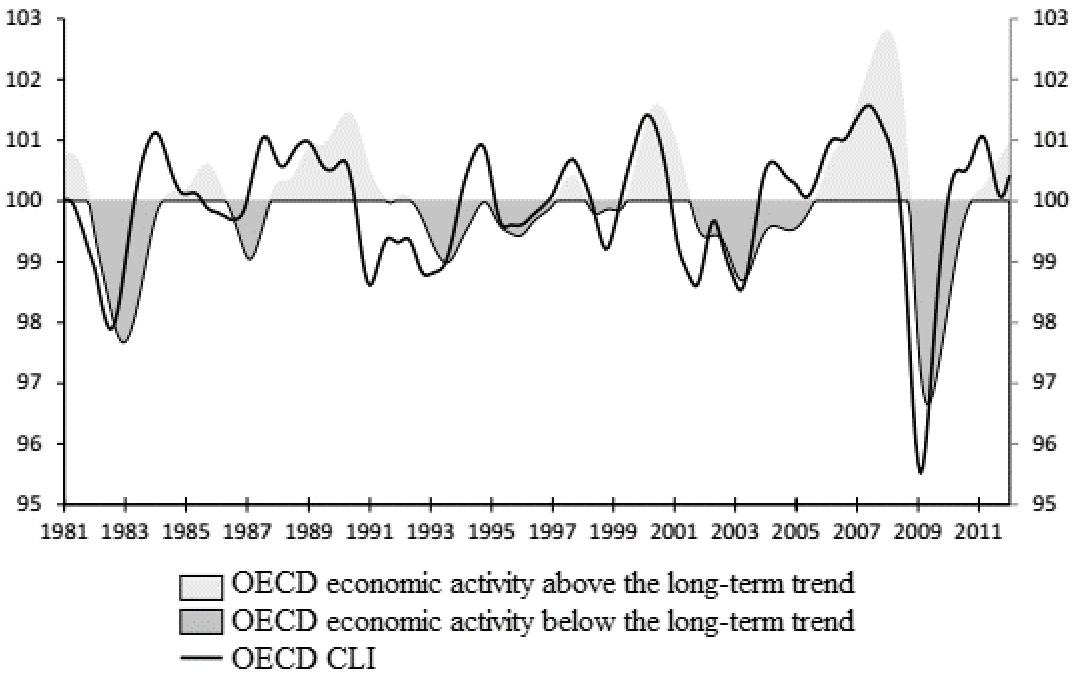
The OECD CLI tracks the Index of Industrial Production, which is usable as a proxy for economic activity in the U.S. (Fulop & Gyomai, 2012). The main reason for the use of this proxy is that GDP data are only available on a quarterly basis or with a delay, while the industrial production data are available monthly. The OECD CLI is composed of economic indicators that behave in a cyclical manner comparable to that of the business cycle. These indicators lead the business cycle and exhibit the cyclical behaviour of the business cycle before the business cycle does so. The OECD CLI is composed by gathering data first, which are then filtered and de-trended, analysed, and combined to one aggregate measure.

Figure 2.3 compares OECD CLI predictions to actual economic activity of OECD countries between 1981 and 2012. We can see that there are strong co-movements between the two. The turning points of the OECD CLI consistently precede those of the actual activity, which indicates that the OECD CLI is an adequate measure of business cycle stages. The OECD CLI aims to precede the movements of the actual business cycle by six to nine months. It is published with a two-month delay because it depends on other institutions to provide necessary data. Adjusted for this delay, the OECD CLI's predictive power is reported to be four to seven months.

Figure 2.3

OECD CLI and OECD economic activity for the OECD area

Unadjusted for publication delay of two months, long-term trend = 100



Reprinted from: "OECD System of Leading Indicators" by Guidetti and Gyomai (2012).

One disadvantage of the use of indices of leading indicators is that the data are prone to revisions. Revisions are due to two reasons: changes in the methodology and data availability. While there have been no fundamental changes to the OECD CLI, the methodology has been subject to improvements over time. Two of major changes were in 2002 and 2008, both of which were aimed at increasing CLI effectiveness and decreasing revisions over time (OECD, 2007, 2008). The second type of revisions takes place in the short run due to new data coming out, and with it changes caused by filtering and de-trending methodology.

Fortunately, the whole time series is recalculated each month since its inception, which means that the impact of these methodological changes is known retroactively. It is possible for us to use the initial OECD CLI time series that was known at a specific period in time when we perform our out-of-sample analysis on that time period. In other words, we perform our out-of-sample analysis with actual data as it was known at that period in time instead of the most recent data concerning that time period, as the former has possibly been revised over time.

2.2 Investment environment

In this section, we discuss the circumstances under which we optimise portfolio performance. We specify these characteristics since they determine model choices later on in this study. We do not choose an investor with a specific background such as a retail investor or an investment professional to keep our findings universally applicable across investor types in the study. Also, we do not want an investor's background to impose restrictions or cause subjective assumptions within the model. The investor has the following goals and characteristics:

1. The goal of our investor is utility maximisation through mean variance optimisation with no other investment goal.
2. Our investor follows the mean-variance utility function of Formula (2.1) (De Goeij, 2016):

   $$U(E(r), \sigma^2) = E(r) - \frac{1}{2} \times A \times \sigma^2 \tag{2.1}$$
3. We do not specify the risk-aversion coefficient A but perform risk-aversion sensitivity analyses where necessary.
4. Our portfolios are restricted from borrowing, short sales are not allowed; the minimum weight of each asset class is 0%.
5. All wealth has to be invested in each time period; the sum of all asset weights has to accumulate to 100%.
6. Our investor is an asset-only investor and does not take liabilities in account, nor investment decision influenced by other owned assets (private property or pension claims do not influence investment decisions).
7. Our investor's utility function is uninfluenced by the time horizon (there is no exit window in the future, and life-cycle investing is irrelevant).
8. Investment decisions are made on a monthly basis, and over a time period of 43 years.
9. This study is focussed on the U.S. market only. This prevents a geographical mismatch between asset classes and of asset classes with the business cycle. Moreover, for the U.S., data are widely available for long time periods, while asset classes are generally liquid

2.3 Asset universe

The first step in asset allocation, is the selection of asset classes to be considered for investments. When we look at literature on dynamic asset allocation, we find that the universe of assets considered changes per study. We determine the universe of asset classes in this study based on a number criteria that have to be fulfilled. These criteria are necessary to be able to implement an investment model that is able to change its asset allocation on a monthly basis, which is elaborated later on in this research. Furthermore, we follow Greer (1997, p.87) who clearly defined an asset class as "a set of assets that bear some fundamental economic similarities to each other, and that have characteristics that make them distinct from assets that are not part of that class".

We use the following criteria to determine our universe of asset classes:

1. Assets are considered to form an asset class if they conform to the definition of Greer (1997).
2. We do not evaluate sub-asset classes, unless there are characteristics that make them fundamentally different from other sub-asset classes or assets not part of that class.
3. Asset classes have to be available for both entry and exit during the whole time period.
4. Asset classes have to be investable and divestible on a monthly basis.
5. Price data has to readily available.

Requirements 1 and 2 are derived from the definition of Greer (1997), while requirements 3, 4 and 5 are required to be able to perform a time-varying asset allocation model. Within this model assets classes have to be able to be bought and sold over a monthly horizon against market prices that correctly represent their value.

We start by evaluation the traditional components of a portfolio, namely equity and bonds (corporate and government), and expand the asset universe by including asset classes that are often referred to as 'alternative assets'. These asset classes are real estate and commodities, and often sub-asset classes such as corporate high yield bonds, inflation-linked bonds, private equity, and hedge funds. In this section we evaluate all these asset classes according to the criteria above. Based on these criteria we determine our investment universe as listed equity, commercial real estate, government bonds, corporate bonds, and commodities. These choices are further elaborated in this chapter. We also provide an overview of literature that investigated how these asset classes behave in relation to the business cycle.

2.3.1 Equity

Literature has found many different ways to divide equity in sub-asset classes, and to diversify within it. In this study we only evaluate private equity as a separate asset class as opposed to stocks (public equity). Private equity is often seen as a separate asset class and found to have fundamentally different characteristics from public assets (Schmidt, 2005; Fenn, Liang, & Prowse, 1997).

We do not create separate asset classes for risk factors such as size and market-to-book value as identified by Fama and French (1993), nor for industries within equities. The economic exposure of these sub-asset classes is not necessarily fundamentally different from each other. Furthermore, these divisions do not create homogenous asset classes as multiple risk factors or industries would create overlap amongst them. We do not look at international diversification possibilities of equity such as geographically or development (frontier, emerging, and developed markets), this study focusses only on the U.S. markets.

Stocks

Stocks are well known to behave in a procyclic manner. This behaviour is mainly driven by changes in the future cash flows of the companies that the stocks represent, and by changes in supply and demand in the stock market. Both factors are found to be positively linked to the business cycle.

When looking at the pricing of stocks, we find that this is mainly driven by the valuation of a company’s cash flows and profitability. This is assessed based on underlying information often referred to as the fundamentals, such as financial statements. Literature found that future cash flows and profitability are positively tied to the business cycle. Siegel (1991) argued that stock prices strongly impacted by the business cycle since economic growth is basis of corporate profits and thus earnings and dividends to stockholders. Hamilton and Longis (2015) found a positive relation between profit margins and the business cycle.

Stock prices are also driven by supply and demand, which change over the business cycle as well. While supply and demand are for a large part driven by the fundamentals that drive stock prices, they are also influenced by investor behaviour. Campbell (1999) suggested that consumers take fluctuations in the economy extremely seriously, which is also reflected in their behaviour on financial markets. Related to this sensitivity is the overreaction of investors in the financial markets, which was first observed by Bondt and Thaler (1985). Campbell (1999) also indicated that risk aversion might increase in bad times, compared to good times. These effects drive the well-established phenomena of flight-to-quality and herd behaviour in the financial markets (Scharfstein & Stein, 1990). Flight-to-quality is the sale of higher risk investments and the purchase of safer assets when fear arises on financial markets.

Both the fundamentals and the behavioural effects drive the procyclic behaviour of stocks. Besides this procyclic tendency, literature found stocks to often lead the business cycle (Moore, 1983; Siegel, 1991; Brocato and Steed, 1998). This indicates that the stock market is more forward looking than the economy.

Private equity

The economic behaviour of private equity differs from public equity, and it is found to add value to asset allocation by Chen, Baierl and Kaplan (2002), and Schmidt (2005) amongst others. However, we decided to not include it as an asset class in this study for two reasons. First, it is not directly investable as an aggregate asset class. Second, investments are illiquid for long periods, sometimes as much as ten years, making them unusable in time-varying asset allocation strategies.

2.3.2 Bonds

The bond market can be divided in two groups: corporate bonds and government bonds. Within government bonds we exclude Treasury Bills (T-Bills), bonds with a maturity shorter than one year, and inflation-linked bonds. T-Bills are used as the risk-free rate which is discussed in Section 3.2. Inflation-linked bonds are excluded since they are relatively new as an asset class. Data on the performance of the aggregate inflation-linked bonds is only available as of March 1997 (Barclays, 2016), which makes them unable to be incorporated in an out-of-sample analysis.

Corporate bonds can be divided in investment grade bonds and high yield (junk) bonds. The difference between these two is the credit rating of the company, and with it its default risk and the compensation for it. As default risk is also incorporated in investment grade bonds we do not follow this division in this study as the two are not fundamentally different, but only have a different impact of the same risk premia. We do not look at emerging market debt as we focus only on the U.S. market.

Government bonds

From this point on, we use the term bonds to refer to government bonds. Opposed to equity, bonds are found to move inversely with the business cycle (Moore, 1983). Brocato and Steed (1998) found that this is caused by the cyclical movement of interest rates and the fixed income nature of bonds. Interest rates are known to behave pro-cyclic; they increase when economic output increases (Friedman, 1986). During downturn we see two phenomena; first, when interest rates decrease, bond prices increase. Second, the demand for bonds increases due to the fixed income nature of bonds, which causes them to be regarded as ‘safe’ assets. We discussed behavioural aspects when we covered the relationship of stocks with the business cycle. The effects we observed there often cause the demand for bonds to increase, as is the case for flight-to-quality, time-varying risk aversion, and herd behaviour in equity sell-offs.

Corporate bonds

From this point on, we use the term credits to refer to corporate bonds. Credits, offer a premium over government bonds called the credit spread. Well recognised is a default premium within credits. The default risk premium is inversely related to the business cycle (Fama & French, 1989). During downturn, equity values decrease resulting in an increase in the risk of default, and as a result an increase in the default risk premium.

However, literature finds excess premium within the credit spread. Different explanations for this excess risk premium can be found in the literature. Elton, Gruber, Agrawal, and Mann (2001) explain the credit spread by three factors: the expected default loss, a tax premium and an excess bond premium they relate to systematic risk. Amato and Remolona (2005) explain the premium by the existence of jump risk within credits. De Jong and Driessen (2008) identified a liquidity risk premium in credit spreads. Corporate bonds are found to have a significant exposure to both liquidity in the equity market and the treasury bond market. Liquidity is positively correlated to the business cycle especially in the equity market, which results in an inverse relation with the business cycle for this liquidity premium. Gilchrist and

Zakrajšek (2012) argued that the excess risk premium reflects the price of default risk rather than the risk of default. Shocks in this excess premium are caused by the risk appetite of the financial sector and the supply of credit, which are both are related to the business cycle. During downturn this excess risk premium increases due to a decrease in risk appetite of the financial sector and, as a result, a contraction in the supply for credit.

Hoevenaars, Molenaar, Schotman and Steenkamp (2008) found that bonds are highly correlated with credits at different horizons with a correlation that is always more than 90%. While both asset classes follow the same pattern, the difference in risk premia make that credits have higher returns, exhibit a stronger cyclical trend, and are more volatile as a result.

2.3.3 Real estate

Within the asset class real estate, a distinction can be made between commercial and residential real estate. In this study, we only focus on commercial real estate. The residential real estate is mostly in the hands of occupiers or residents (Doeswijk, Lam, & Swinkels, 2011), and therefore not investable as an aggregate to investors. The residential real estate market is also not investible or divestible on a monthly basis. Investing in commercial real estate is mostly done through Real Estate Investment Trusts (REITs). These publicly-traded entities mainly buy and manage income-producing properties and distribute the profits to their shareholders. Real estate investing through REITs allows for liquid investing in real estate as opposed to direct investments.

Real estate returns are found to behave differently at times of high GNP growth compared to low GNP growth (Chiang, Lee, & Wisen, 2004). Quan and Titman (1999) found that rent is the primary determinant of real estate values and that rent prices is strongly correlated with GDP growth. Besides GDP growth, real per capita consumption and the real T-bill rate influence real estate pricing (Naranjo & Ling, 1997).

If we compare the returns of real estate with equity, Sagalyn (2009) found that REITs have lower volatility and higher returns than stocks in periods of high economic growth. We can conclude that, besides the shared exposure to economic activity, interest rates, and consumption, literature states that real estate and equity each have their unique characteristics, and that they behave differently over the business cycle.

2.3.4 Commodities

Commodities are very different from other asset classes, they are not claims on long-lived corporations or provide resources for firms to invest, but comprise physical goods. Commodities can be divided across five main groups: energy, precious metals, industrial metals, livestock and meat, and agricultural commodities. In this research we assess them as an aggregate asset class, and include them as such in asset allocation. This approach is similar to that in the literature we discuss in Section 2.4. Commodities are mostly traded through futures and forward contracts that allow people to buy or sell a commodity at a specified time in the future at a price that is agreed upon now. The exchange of the good, or the financial settlement of the contract, happens only at the specific time in the future that is agreed upon. There is no exchange of money or assets when engaging in the contract in general.

Industrial production relates commodities directly to the business cycle (Pindyck & Rotemberg, 1988). Industrial production, a proxy for the aggregate economic activity, drives the supply and demand of commodities. For example, an increase in industrial production leads to a direct increase in demand for industrial inputs such as metal and oil. It also leads to an increase in consumer income, which boosts demand for cacao and wheat (Pindyck & Rotemberg, 1988). On the other hand, oil and energy-related commodity prices are found to increase in the early stages of a recession (Gorton & Rouwenhorst, 2006).

Literature also found that future supply and demand for commodities is influenced by interest rates. Interest rates are known to behave procyclic; they increase when economic output increases (Friedman, 1986). Changes in interest rates influence economic expectations, which alter expectations on future demand of commodities. Increase in interest rates also decrease capital investments of commodity suppliers, decreasing future supply, and they increase the cost of commodity storage as returns on holding capital increase compared to holding or storing commodities (Pindyck & Rotemberg, 1988).

These are the main many relations of commodities with the economy as a whole, and the business cycle. We find that not all effects have the same direction. Erb and Harvey (2006) argued that individual commodities are not homogeneous and that their high volatility and low mutual correlations result in high diversification benefits with each other. Including commodities as one asset class means that this asset class incorporates some diversification benefits by itself. This could possible explain the low correlation of commodities with other asset classes that is found in literature.

Gorton and Rouwenhorst (2006) found that commodities do not follow the same cyclical variation that is observed in stock and bond returns, while Greer (2002) found them to be negatively correlated to equities and bonds. Conover, Jensen, Johnson and Mercer (2010) confirm these findings and again conclude that commodities provide benefits to asset allocation especially when interest rates are rising. All these studies confirm the value of commodities to portfolio performance, and give commodities an important place in asset allocation over the business cycle.

2.3.5 Hedge funds

Another asset class to consider is hedge funds. Hedge funds are included as an asset class by Bekkers, Doeswijk, and Lam (2009) and by Hoevenaars, Molenaar, Schotman and Steenkamp (2008). However, we do not see hedge funds as an asset class. Hedge funds deploy strategies that invest in the assets we already included in this research. Hedge fund investments are an investment in the skills and strategies of portfolio managers and not in a specific group of assets that have shared characteristics that are economically different from our spectrum of asset classes. Other reasons to exclude hedge funds are that they are not investable as an aggregate asset classes, they are often not investable or divestible on a monthly basis, price data is often biased (Bekkers, Doeswijk, & Lam, 2009), and historic data is limited.

2.4 Previous research

In this section we discuss existing literature that found that expected returns and volatilities of asset classes and correlations between asset classes are time-varying, related to the business cycle, and that anticipation could lead to increased portfolio performance. Fama and French (1989) are some of the first to elaborate on the cyclical behaviours of asset classes. They find a clear business-cycle-based pattern in the expected returns of common stocks and long-term bonds.

Siegel (1991) was one of the first to look into the combination of the business cycle and asset allocation. Siegel used NBER recessions and expansions to create a strategy that switches the asset allocation from stocks to bonds over the business cycle. Siegel's findings are only applicable to ex-post analysis, as a result of the use of NBER business cycles (Chapter 2.1). Siegel finds that the anticipation of the business cycle adds value over static buy-and-hold strategies. More specifically, he finds additional value in leading the business cycle. With leading the business cycle, he means adjusting asset allocations to anticipate the next stage in the business cycle before the economy actually goes there. He finds on average 1% of additional annual returns for each month that an investor leads the economy. He identifies the optimal amount of time to switch allocations before peaks to be 5 months and for troughs of 1.6 months.

Brocato and Steed (1998) introduced portfolio optimisation over the business cycle based on mean-variance optimisation as it was introduced by Markowitz (1952). They used the NBER data to measure the business cycle comparable with the approach of Siegel (1991). Consequently, they could only perform ex-post analysis and draw conclusions with hindsight. Brocato and Steed found both volatilities and average returns to be different per stage of the business cycle. Correlations are found to increase during recessions when compared to expansions. Most importantly, mean-variance efficiency was improved by modifying asset weights to accommodate changes in the NBER business cycle.

Jensen and Mercer (2003) added to Brocato and Steed (1998) by performing both in-sample and out-of-sample analyses based on the monetary cycle instead of the NBER business cycle. The monetary cycle allowed them to determine ex-ante turning points that precede those of the business cycle. Their study finds that there are large differences in the returns of assets, and smaller differences in volatilities over both the business cycle and the monetary cycle. There are also differences in correlations over the cycles, but these are smaller in comparison. Furthermore, adjusting for the monetary cycle results in higher risk-adjusted returns than those that resulted from adjusting for the NBER business cycle or buy-and-hold strategies. In their out-of-sample analysis, Jensen and Mercer (2003) found that portfolio rebalancing based on monetary-cycle turning points increased performance over the business-cycle approach.

Van Vliet and Blitz (2009) investigated risk and return characteristics of asset classes and found four different regimes within them. They relate these regimes to the movement of the business cycle. Not only asset risk and return, but also correlations exhibit cyclical movement over these regimes. While they did not check for significance, they found that diversification benefits dilute when economic growth decreases. They also found a clear variation in the total return and the accompanying risk that can be achieved under each regime; portfolios do not only have lower returns but also become much more risky when economic growth decreases. They found that changing allocations according to the movement of the business cycle can stabilise portfolio risk and can even enhance returns.

Dzikevičius and Vetrov (2012) combined the business cycle with asset allocation and portfolio optimisation. They used the OECD CLI to optimise portfolios in an out-of-sample analysis. Since they used the OECD CLI, they also distinguished the four-stage business cycle that was introduced by Van Vliet and Blitz (2009). Dzikevičius and Vetrov (2012) confirmed time-varying risk and return properties of assets. Furthermore, they found that strategies that are based on cyclical variations in asset allocation outperform passive strategies. Unfortunately, Dzikevičius and Vetrov (2012) only look at the OECD CLI as a business cycle predictor. They do not look at the actual business cycle and the potential that is available when adjusting for the business cycle in portfolio optimisation. Furthermore, Dzikevičius and Vetrov (2012) do not appear to adjust for OECD CLI revisions.

In this study, we add to existing literature in a few areas. First, we take a step-by-step approach to determine the optimal way to incorporate the business cycle into portfolio optimisation. We start by an extensive analysis of the behaviour of asset classes over the four stages of the actual business cycle, and more thoroughly investigate the relationships between assets classes in terms of correlations and their volatilities over time. We continue by investigating the in-sample potential of incorporating our findings of the previous part into portfolio optimisation. Then, we develop two out-of-sample models to capture this potential. We compare them to each other, and to their in-sample benchmark to assess how much of the potential of business-cycle-based portfolio optimisation they capture.

Jensen and Mercer (2003) are the only ones to have followed this complete step-by-step approach. They did this for the monetary cycle, while we focus on the business cycle. Besides our step-by-step approach we add to the early literature in this field by using a four stage business cycle, and by doing out-of-sample analyses. We add to more recent literature by using the OECD CLI out of sample and comparing it to its in-sample potential. We also add by using a mean-variance utility function that incorporates risk aversion to optimise portfolios, instead of only using Sharpe ratio optimisations that is used in previous research. Furthermore, we are the first to use the Black-Litterman model in addition to a model that switches between allocations over the business cycle. The Black-Litterman model accounts for drawbacks of the mean-variance portfolio that switches allocations.

Chapter 3

Data

3.1 Data sources

This study focuses only on the U.S. and its markets. We use U.S. Dollar (USD) denominated monthly total return data and USD denominated market capitalisations. We focus only on the U.S. since it has the longest data series of almost all asset classes, and it prevents geographical mismatch. An exception is the asset class commodities, which always operates on a global scale. Table 3.1 provides an overview of our variables, indices through which they are measured, data sources and available time periods. From now on, we refer to public equity as stocks, government bonds as bonds, and corporate bonds as credits.

For each asset class, data from 1973 onwards is available. The period of the sample analysed spans 43 years; from January 1973 to December 2015. This time period comprises six business cycles, the last of which is still ongoing according to official NBER data. The index values of each asset class over time are shown in Figure A2 in this chapter's appendix.

Table 3.1
Variables and data sources

Asset class	Index	Source	Data availability
Public equity (Stocks)	Wilshire 5000	Datastream	01/1971-09/2016
Real estate	FTSE NAREIT U.S. All Equity REITs	National Association of Real Estate Investment Trusts	01/1972-09/2016
Government bonds (Bonds)	Bloomberg Barclays U.S. Treasury Bond Index	Datastream	01/1973-09/2016
Corporate bonds (Credits)	Bloomberg Barclays U.S. Corporate Bond Index	Datastream	01/1973-09/2016
Commodities	S&P Goldman Sachs Commodity Index	Datastream	01/1970-09/2016
Other variables			
Risk-free rate	3-Month Treasury Bill: Secondary Market Rate	Federal Reserve Bank of St. Louis (FRED)	01/1934-09/2016
Business cycle indicator	U.S. GDP ratio-to-trend	OECD	02/1947-06/2016
Leading business cycle indicator	U.S. Composite Leading Indicators	OECD	01/1955-07/2016

3.2 Index choice and characteristics

We retrieved all index data from total return indices; this means that all pay-outs the index generates are reinvest (such as coupon payments and dividends). We first discuss the commodity index, which is different from the other indices. The commodity index tracks the production of assets that are consumable or transformable into other assets through derivative products on those assets. The index consists of commodity futures whose weights are production weighted over the last five years. We use the Goldman Sachs Commodity Index since it represents the majority of open interest in the future market (Masters, 2008).

The other indices are much more similar as they all directly invest in the assets the indices represent. They are all market capitalisation weighted and free-float adjusted. Free-float adjusted means that the indices only consider the market capitalisation of outstanding shares or bonds that are available to investors, which causes their index to represent the asset universe as it is available to investors. The investments of all indices are also subject to minimum size and liquidity requirements.

All indices try to capture the largest possible part of the market they represent. The stock index comprises the whole listed U.S. equity market. The real estate index comprises all taxable REITs, except mortgage REITs, with more than 50% of total assets in qualifying real estate assets. The bond index measures the performance of all fixed-rate nominal debt issued by the U.S. Treasury. The maturity of bonds changes if the maturity of nominal debt outstanding changes as can be seen in Figure A1 in this chapter's appendix. T-Bills, inflation-linked bonds, and bonds issued by the state or local government, and from government agents are excluded. All included bonds are investment grade. The credit index measures the performance of the aggregate fixed-rate taxable investment-grade corporate bond market with at least one year outstanding till maturity.

To determine the risk-free return, we use the rates offered on 3-month T-Bills in the secondary market, which is the rate that is actually available to investors. The primary market rate is the rate as set by the Federal Reserve System, which is uninfluenced by supply and demand. T-Bills issued by the U.S. Treasury are regarded as risk-free investments. We use specifically short term T-Bills as a risk-free rate since they quickly catch up with changes in macroeconomic indicators (Hoevenaars, Molenaar, Schotman, & Steenkamp, 2008). This makes them a good proxy for the risk-free rate on short horizons.

3.3 The market portfolio

We compare both our in-sample and out-of-sample portfolios to a market portfolio. The market portfolio considered in this study only comprises the five asset classes we consider for the other portfolios. The historic market capitalisations and the historic market portfolio for the whole time period of 43 years can be found in Figures A3.1 and A3.2, respectively (Appendix - Chapter 3).

Our U.S. stock market capitalisation is measured through the market capitalisation of the Wilshire 5000 as this index comprises all listed equity. The U.S. real estate market capitalisation is obtained from the National Association of Real Estate Investment Trusts. These data are only available on an annual basis, which we have interpolated to obtain monthly market capitalisations. Since the real estate market capitalisation has been small historically (0.1–3.0% of the total market), we expect the impact of interpolation to be negligible. Our bond market capitalisation covers all bonds issued by the U.S. government. The credits market capitalisation only covers investment grade corporate bonds since we excluded non-investment grade bonds from the current study. Both our bonds and credits capitalisations are obtained from the corresponding Bloomberg Barclays Indices obtained through Datastream.

We do not include commodities in our market portfolio due to two reasons. First, commodities are considered to be an alternative asset class that has historically not always been part of investment portfolios. Second, it is very difficult to create reliable estimates of the commodity market size. Investments in commodities are mostly done through derivative products. Measuring the market in terms of the size of the future and forward market is not necessarily a good reflection of the size of the market for actual commodities. Another possibility is to assess the market weight of commodities by looking at worldwide inventories of commodities. However, these data have to be obtained on a per commodity basis and are not aggregated. Obtaining reliable inventory data for each commodity in the market over the full 43-year time period is not possible; therefore, we do not include commodities in the market portfolio.

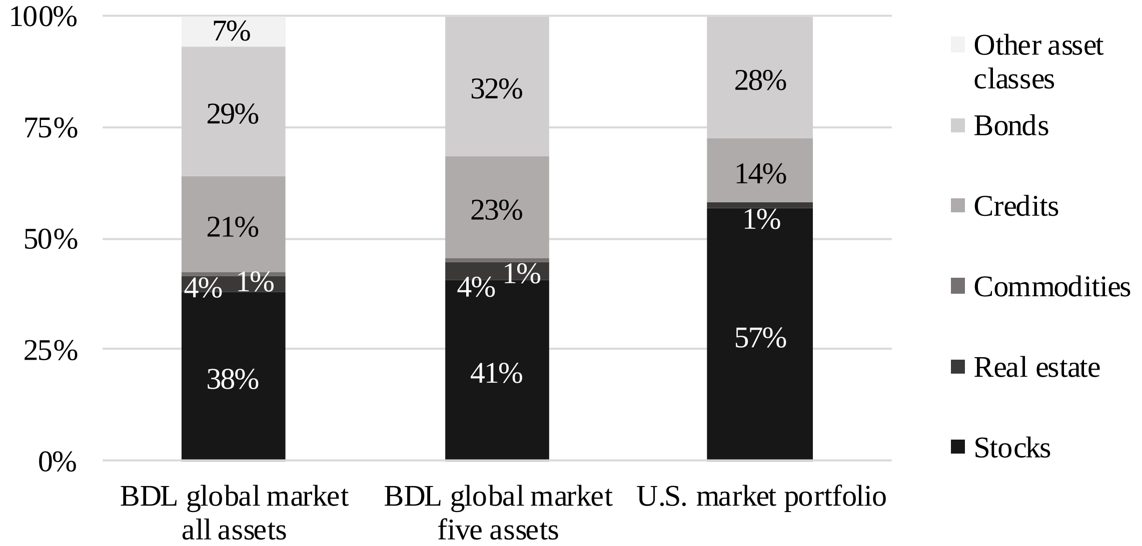
We compare our market portfolio to that of Bekkers, Doeswijk and Lam (2009) in Figure 3.1. Bekkers, Doeswijk and Lam (2009) use a large variety of data sources to estimate the global market portfolio and also use the market portfolio in mean-variance optimisation. We conclude that the asset classes in our study cover 93% the market capitalisation of all asset classes in the global market portfolio of their research. We find that our allocation to bonds is comparable, while the allocations to credits and real estate are smaller in our market portfolio. Stocks have a significantly larger allocation in the market portfolio we determine. Besides by the focus on a different market, we expect this difference to be driven by the exclusion of sub-investment grade corporate bonds in our study.

Bekkers, Doeswijk and Lam (2009) estimate a very small weight for commodities in all assets the market portfolio (< 1%). This indicates that excluding commodities from our market portfolio does not have a substantial impact on the performance of the market portfolio.

Figure 3.1

Market portfolio asset weights, 2008 end of year

The global market portfolio of Bekkers, Doeswijk and Lam (2009) at 2008 year end is represented in the first column. They distinguish 9 asset classes, while we assess only 5 asset classes. The asset classes we do not include are inflation linked bonds, corporate high yield bonds, hedge funds, and private equity. The market weights for only these 5 assets are represented in column 2. Our market portfolio for the U.S. market can be found in column 3.



3.4 Business cycle measurement

The OECD GDP ratio-to-trend and the OECD CLI amplitude-adjusted measurements of the business cycle have to be transformed from their values to business cycle stages. This is done through the following classifications:

- Expansion: indicator value above 100 and increasing
- Downturn: indicator value above 100 and decreasing
- Slowdown: indicator value below 100 and decreasing
- Recovery: indicator value below 100 and increasing

These classifications are used to label each month according to the business cycle stage corresponding with that month. Subsequently, this allows us to pool monthly returns for each business cycle stage. Consequently, we are able to compare asset classes in terms of return, volatility and Sharpe ratio during each business cycle stage. This approach is identical to the approach used in previous studies (Brocato & Steed, 1998; Jensen & Mercer, 2003; Dzikevičius & Vetrov, 2012). The values of the indices are compared later on in this report (Figure 5.2).

Chapter 4

Asset class behaviour

4.1 Returns and volatilities

The first step in our analysis is the assessment of historic returns, volatilities and correlations over the business cycle. All returns and volatilities are calculated on a monthly basis. Since our index data are on a total return basis, they are already adjusted for dividends and other pay-outs (which are reinvested). We calculate asset returns using Formula (4.1), where $R_{j,t}$ stands for the return of asset j in month t. P_{t+1} and P_t stand for the index values at the beginning of months t and $t+1$ respectively.

$$R_{j,t} = (P_{j,t+1} - P_{j,t}) / P_{j,t} \tag{4.1}$$

In our analysis, we focus on the excess returns, which are asset returns compared to the risk-free return. This allows us to compare the compensation for risk over time instead of the absolute returns. Excess returns are calculated using Formula (4.2), where $ER_{j,t}$ stands for the excess returns of asset j in period t, and $R_{f,t}$ stands for the risk-free rate offered in the beginning of that month.

$$ER_{j,t} = R_{j,t} - R_{f,t} \tag{4.2}$$

We compare asset performance in terms of average excess return, volatility and Sharpe ratio. Average excess returns and volatilities are calculated on a monthly basis, but are annualized to allow for easy interpretation. Average excess returns are annualized through Formula (4.3), and volatilities through Formula (4.4). Sharpe ratios is used as a measurement for risk-adjusted returns over a time period T and are calculated using Formula (4.5).

$$\text{Annual } ER_j = (1 + \text{monthly } ER_j)^{12} - 1 \tag{4.3}$$

$$\text{Annual volatility}_j = \text{monthly volatility}_j * 12^{1/2} \tag{4.4}$$

$$\text{Sharpe ratio}_{j,T} = \text{Annual } ER_{j,T} / \text{Annual volatility}_{j,T} \tag{4.5}$$

We perform T-tests and F-tests to be able to draw conclusions on the behaviour of asset classes over the business cycle. The T-tests are used to test whether the average excess returns of an asset significantly differ during a business cycle stage as compared to those during the entire cycle. Similarly, F-tests are used to test if volatilities significantly differ in each business cycle stage as compared to the full period.

Table 4.1 presents risk and average excess returns' characteristics of all our assets over the business cycle. We conclude that assets show both economically large and statistically significant differences in their behaviours over each business cycle stage, when compared to the whole cycle in terms of both risk and volatility. This is also reflected in the large differences in Sharpe ratios over the business cycle. However, it appears that this effect is stronger for returns than for volatilities. When we look at volatilities, we find that they move in a similar manner over business cycle stages when compared among asset classes. Commodity returns are always most volatile, while bonds and credits are always least volatile. Regarding the returns over the business cycle, we find that real estate has the highest returns over the whole cycle. However, if we look returns per stage, it only has the highest return of all asset classes during recovery. Stocks show the highest return during expansion, commodities during downturn, and credits during slowdown. This is also reflected in the Sharpe ratios; each stage has a different asset with the highest Sharpe ratio, which we find to be mostly driven by average excess returns.

We find that average returns are lowest during expansion and downturn, and highest during slowdown and recovery for all asset classes, except for commodities. Volatilities are found to be highest during downturn and slowdown for all asset classes. Assets are thus most volatile when the economy's performance is relatively negative. Assets perform best in terms of Sharpe ratio during slowdown and recovery when average excess returns are highest, with the exception of commodities. This confirms the findings of Blitz and Van Vliet (2009). We find again that average excess returns have the largest effect on asset performance when compared to volatilities.

When we compare asset classes with each other, we find that stocks and real estate have the highest average excess returns over the whole period. Both assets perform relatively well during slowdown and recovery when compared to during expansion and downturn in terms of Sharpe ratio. Bonds and credits are much less volatile than the other assets and are the best-performing assets in terms of Sharpe ratio over the whole sample. Both assets have negative historic excess returns during expansion and both perform best during slowdown. Commodities have a very different return structure compared to the other assets. They perform best during recovery and worst during slowdown. Over the full period, overall returns are low, and commodities are always the most volatile asset class.

Interest rates appear to partially drive the cyclical behaviour of excess returns. On average, risk-free rates are highest during expansion and downturn, when excess returns are lowest. We see the opposite effect during slowdown and recovery. However, we find that the cyclical effect in asset returns is much larger than just the effect of interest rates. This can be observed when looking at the risk and return characteristics of total returns presented in Table A1 in this chapter's appendix. We find that all returns still exhibit significant cyclical behaviour over the business cycle.

Table 4.1

Returns and volatilities based on excess returns, 1973 - 2015

	Expansion	Downturn	Slowdown	Recovery	Full period
Stocks					
Arithmetic annual excess return (%)	2.28 *	-4.80 ***	8.97 **	13.94 ***	5.04
Annualized volatility (%)	15.35	16.76	19.82 ***	13.07 ***	16.40
Sharpe ratio	0.15	-0.29	0.45	1.07	0.31
Real estate					
Arithmetic annual excess return (%)	1.19 ***	1.08 ***	9.09	16.74 ***	6.85
Annualized volatility (%)	13.41 ***	15.85	23.81 ***	15.22 **	17.46
Sharpe ratio	0.09	0.07	0.38	1.10	0.39
Bonds					
Arithmetic annual excess return (%)	-0.32 ***	1.68	6.77 ***	1.89	2.36
Annualized volatility (%)	4.39 ***	6.01 **	5.59	4.65 *	5.19
Sharpe ratio	-0.07	0.28	1.21	0.41	0.45
Credits					
Arithmetic annual excess return (%)	-0.36 ***	-2.51 ***	10.36 ***	4.35 **	2.81
Annualized volatility (%)	5.27 ***	8.90 ***	7.89 *	5.91 ***	7.14
Sharpe ratio	-0.07	-0.28	1.31	0.74	0.39
Commodities					
Arithmetic annual excess return (%)	1.31	3.54	-6.49 ***	4.91 **	0.79
Annualized volatility (%)	19.39	24.04 **	23.89 **	16.71 ***	21.03
Sharpe ratio	0.07	0.15	-0.27	0.29	0.04
Airthmetic annual risk free rate (%)	5.29	6.58	4.39	3.41	4.88
% of time in this economic stage	28	23	24	26	-
# Observations	144	117	123	132	516

***, **, * Significantly different from the full period statistic at respectively the 1% , 5% or 10% level

4.2 Correlations

In Table 4.2, we present the monthly excess return correlations for all asset classes over the business cycle. These correlations provide insight into the co-movement of assets and can be used to assess changes in diversification benefits over the business cycle. To test if correlation coefficients are different during business cycle stages compared to the full period, we use the Fisher z-transformation following Jensen and Mercer (2003). The Fisher z-transformation transforms correlation coefficients to z-scores using Formula (4.6) and standard errors are calculated using Formula (4.7). Two correlation coefficients i and j are compared using hypothesis testing with Formula (4.8) as a test statistic. In these formulae, n stands for the sample size.

$$z = ½ \ln((1+r)/(1-r)) \tag{4.6}$$

$$SE = 1 \,/\, \sqrt{}(n-3) \tag{4.7}$$

$$z = (z_i - z_j)/\sqrt{}(\,1/(\,n_i - 3) + 1/(n_j - 3)) \tag{4.8}$$

We find only a few correlation coefficients to be significantly different during business cycle stages when compared to the full period. Almost all statistically significant correlations involve credits and another asset, or commodities and another asset. Concerning credits, we do not see sufficient significant evidence to draw conclusions on cyclical trends. For commodities, correlations with stocks and real estate are lower during expansions, and correlations with bonds and credits are lower during recovery when compared to the full period. We find no evidence supporting the findings of previous studies that correlations between asset classes increase during downturn and slowdown.

When we compare the correlations amongst asset classes, we find that commodities have low correlations with all other asset classes, which make commodities a good diversifier. This could be due to the global nature of commodities, while all other asset classes are only U.S. based. Stocks and real estate have relatively high correlations with each other; the same goes for bonds and credits. Correlations between stocks and real estate, and between bonds and credits are found to be low. We do find that credits have a clearly higher correlation with stocks than bonds do, which reflects their relationship with the performance of corporations. The relationship between stocks and bonds is very low as is found in all previous studies.

Table 4.2

Monthly excess return correlation coefficients, 1973 - 2015

	Expansion	Downturn	Slowdown	Recovery	Full period
Stocks and:					
Real estate	0.562	0.629	0.702 *	0.553	0.629
Bonds	0.003	0.174	-0.038	0.090	0.058
Credits	0.126 **	0.324	0.366	0.329	0.305
Commodities	-0.011 **	0.246	0.284	0.256	0.195
Real estate and:					
Bonds	0.119	0.132	-0.012	0.094	0.073
Credits	0.242	0.213	0.357	0.334	0.294
Commodities	-0.087 ***	0.041	0.392 ***	0.184	0.169
Bonds and:					
Credits	0.919 ***	0.841	0.726 ***	0.860	0.822
Commodities	-0.019	-0.057	-0.091	-0.271 ***	-0.103
Credits and:					
Commodities	-0.04	0.04	0.06	-0.160 *	-0.011

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

4.3 Market betas

Table 4.3 presents the market betas of each asset class with the market portfolio over the full period and over each business cycle stage. The beta of asset *j* with the market *m* is calculated through Formula (4.9). Except for stocks, we find market betas to significantly differ over the business cycle stages when compared to the full period. We find stocks to consistently have the highest beta over all business cycle stages. This can be easily attributed to the fact that the market portfolio consists of 66% stocks on average (Figures A3 and A4 in this chapter's appendix).

$$\beta_j = \frac{cov_{j,m}}{var_m} \quad (= \frac{\rho_{j,m} * \sigma_j}{\sigma_m}) \tag{4.9}$$

For other asset classes, we find that the magnitude of their market beta is mainly driven by their correlation coefficient with stocks. Real estate has a relatively high beta that reflects its high correlation with stocks (Table 4.2). Likewise, we find bonds and credits to have low market betas that reflect their low correlation with stocks. Interesting is the negative market beta of commodities during expansion, which is significantly different from its behaviour during the other stages.

While most market betas significantly differ over the business cycle, we find that it is difficult to determine a clear pattern over the business cycle. We only find that betas are lowest during expansion for all asset classes with significant differences over the business cycle. During the other stages, there is no uniform increase or decrease in the market betas of all asset classes when compared to the full period.

Table 4.3
Market betas, 1973 - 2015

	Expansion		Downturn		Slowdown		Recovery		Full period
Stocks	1.42		1.33		1.46		1.43		1.40
Real estate	0.74	***	0.80	***	1.22	***	0.95		0.95
Bonds	0.05	***	0.15	***	0.05	***	0.15	***	0.09
Credits	0.12	***	0.32	*	0.30		0.33	**	0.27
Commodities	-0.07	***	0.45	**	0.44	*	0.30		0.28

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

4.4 Behaviour over business cycles

In the previous sections, we have compared asset class performances among classes and per business cycle stage over our whole sample period. In this section, we analyse asset class performances over the business cycles in our sample. Table 4.4 presents average excess returns per asset class per business cycle, while Table 4.5 presents volatilities per asset class over the business cycles. We exclude the second business cycle from our comparison since its data consists of 28 observations, which we deem too low to draw statistically sound conclusions from.

When we look at Table 4.4, we clearly see that the risk-free rate decreases since the third business cycle. Absolute returns (unadjusted for the risk-free rate) are, therefore, much higher in the early cycles of our sample compared to the more recent cycles. However, this does not affect our study since we use excess returns.

When we compare the excess return per stage to those over the full period, we find that real estate and stocks have high returns in general, but that these are not consistent over all business cycles. The returns of bonds and credits are more stable over time compared to the other asset classes. There are a few outliers such as the negative returns on stocks and credits in the first cycle, the high returns on stocks during before dot.com bubble, the high return of real estate before the most recent financial crisis, and the strong negative returns on commodities driven by the price decrease of energy commodities after the financial crisis. Remarkable is the excess return of 5.20% for real estate after the crisis, this is caused by the strong recovery in (listed commercial) real estate after 2009 as can be observed Figure A2 in the appendix of Chapter 3.

Table 4.5 indicates that volatilities significantly differ over individual business cycles when compared to the full-period volatilities. However, when comparing assets with each other, we find that commodities are generally the most volatile asset class, followed by real estate and stocks. Bonds and credits have consistently low volatilities. When we compare cycles with each other, we find that the first and sixth cycles are most volatile, while the fourth and fifth are least volatile. While some cycles are more volatile than others, a cycle's level of volatility appears to influence all asset classes in a comparable manner.

We conclude that not all business cycles are equal; business cycles differ in length and in terms of macroeconomic characteristics (for example, interest rates, inflation, GDP growth rates, employment rates and the expectation of future business conditions). Furthermore, returns of assets are strongly influenced by events such as the dot.com bubble and the more recent real estate bubble. Lastly, we find that some business cycles are more volatile than others across all asset classes.

Table 4.4

Average excess returns per business cycle, in %, 1973 - 2015

	Risk-free rate	Average annual excess returns: Real estate	Stocks	Bonds	Credits	Commodities	n #	Time period mm/yy
Full period	4.88	6.85	5.04	2.36	2.81	0.79	516	01/73 - 12/15
Cycle 1	6.29 ***	2.84	-2.57 **	0.09 ***	-0.26 **	5.45	65	06/73 - 10/78
Cycle 3	8.37 ***	4.89	5.56	4.15 ***	5.73 ***	3.16	108	03/81 - 02/90
Cycle 4	4.83	5.37	11.98 ***	2.83	3.21	1.47	123	03/90 - 05/00
Cycle 5	3.02 ***	15.38 ***	0.62 **	2.87	3.78	5.94	88	06/00 - 09/07
Cycle 6	0.33 ***	5.20	5.44	3.74 **	5.20 **	-13.01 ***	99	10/07 - now

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Table 4.5

Annualized volatilities per business cycle, in %, 1973 - 2015

	Risk-free	Real estate	Stocks	Bonds	Credits	Commodities	n	Time period
Full period	-	17.46	16.40	5.19	7.14	21.03	516	01/73 - 12/15
Cycle 1	-	16.21	18.87 *	3.50 ***	7.56	25.02 **	65	06/73 - 10/78
Cycle 3	-	11.20 ***	16.55	6.52 ***	8.64 ***	12.64 ***	108	03/81 - 02/90
Cycle 4	-	12.43 ***	12.69 ***	4.22 ***	4.87 ***	17.26 ***	123	03/90 - 05/00
Cycle 5	-	14.96 **	14.28 **	4.64 *	4.58 ***	21.47	88	06/00 - 09/07
Cycle 6	-	27.93 ***	20.10 ***	4.51 **	6.57	27.30 **	99	10/07 - now

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

4.5 Conclusions on asset class behaviour

In this chapter, we identify cyclical behaviour in asset classes' risk and return characteristics over the business cycle. During each business cycle stage different asset classes perform best in terms of both risk and return. We find that average excess returns are a much larger driver of changes in risk-adjusted returns than volatilities are. We do not identify cyclical behaviour between asset classes in terms of correlations and only partially in market betas. The observed cyclical behaviour in average returns and volatilities indicates that portfolio performance can be enhanced when allocating dynamically over the business cycle. Changing asset allocation for each business cycle stage makes it possible to invest in asset classes when their excess returns are expected to be highest, and volatilities are expected to be lowest.

We find a strong relationship between stocks and real estate, and between bonds and credits in the co-movements of average returns and volatilities. We also find high correlations between these two groups. Real estate offers higher average excess returns and volatilities when compared to stocks, we find the same behaviour when we compare credits to bonds. Commodities have low average excess returns and high volatilities in general, but also exhibit low levels of correlation and co-movement with other assets. Commodities potentially act as a diversifier in portfolios, which is in line with Greer (2002), and Hoevenaars, Molenaar, Schotman, and Steenkamp (2008).

We conclude by observing that not all business cycles are created equal; they differ in length and macroeconomic characteristics. We also find that not all asset classes have the same behaviour over each individual business cycle. Regardless of these observations, in the next chapter we find that there is potential to improve portfolio performance by allocating dynamically over the business.

Chapter 5

In-sample analysis

In Chapter 4, we found that asset classes exhibit cyclical behaviour over the business cycle. In this chapter, we analyse the potential of business-cycle-based portfolio optimisation that incorporates these observations. We do this by performing an in-sample analysis, which is based on ex-post data. The methodology of this analysis is outlined in Section 5.1, and the results are in Section 5.2. In Section 5.3, we assess the potential of leading the business cycle, and in Section 5.4, we investigate the possibility of doing so with use of the OECD CLI. For all in-sample analyses in this chapter, we assume excess returns, volatilities, correlations among asset classes, and business cycle stages to be known.

5.1 Methodology

In our in-sample analysis, we create optimal portfolios over our sample period based on all the data we have available today. We calculate the optimal portfolios using mean-variance optimisation as pioneered by Markowitz (1952). This approach is similar to that of previous studies (Brocato & Steed 1993; Jensen & Mercer, 2003; Dzikevičius & Vetrov, 2012). We follow the mean-variance optimisation approach as described by De Goeij (2016).

For our mean-variance approach, we take an investor with a mean-variance utility function as defined by Formula (5.1) in matrix notation. Here, w is a k-dimensional vector that represents the portfolio weights in each of the k risky assets, where w' is the transposed version of this vector. The parameter μ^e is a k-dimensional vector that represents the expected excess returns of these risky assets. Their multiplication $w'\mu^e$ represents the expected excess return of the portfolio's investment in risky assets. The risk aversion of the investor is incorporated through the risk-aversion coefficient A. $w'\sum w$ represents the variance of the portfolio that invests in the k risky assets, where $\sum$ is the k × k variance-covariance matrix of those assets. This problem can be solved by setting the first-order condition of w to 0 as defined in Formula (5.2). The optimal asset weights in each risky asset is expressed by w^*. We have two constrains that are denoted by Formulae (5.3) and (5.4). These constraints prevent short selling and require all wealth to be invested each period, which results in the optimal portfolio that invests only in risky assets w^*.

$$\text{Max } \mathrm{U}(\mathrm{E}(r_c), \mathrm{Var}(r_c)) = \text{Max } [\, r_f + w'\mu^e - 1/2 \times A \times w' \textstyle\sum w \,] \tag{5.1}$$

$$w^* = A^{-1} \textstyle\sum^{-1} \mu^e \tag{5.2}$$

$$w_j^* \geq 0 \tag{5.3}$$

$$\textstyle\sum w_j^* = 1 \tag{5.4}$$

Within this study we compare w^* between different models instead of w' in some cases. This comparison allows to evaluate differences in asset allocation without the interference of risk-free assets. w^* Represents the optimal allocation to risky assets, calculated by maximising the Sharpe ratio. w' Represents the optimal allocation that maximises the mean-variance utility function and allows for an investment in risk-free assets. The relative allocation between risky assets only does not change between w^* and w', only the total allocation to risky assets differs.

In this in-sample approach, we generate optimal mean-variance portfolios over the whole time period of 43 years. We compare three different portfolios. We first create two fixed weight portfolios: the 'fixed weight portfolio' and the market portfolio. These are passive investment schemes unaffected throughout the sample period providing a 'neutral' benchmark uninfluenced by restrictions or subjective views. The fixed weight portfolio is the optimal asset allocation over the whole time period without changes over time. This portfolio is only rebalanced for gains and losses that influence asset weights; its asset allocation starts each month with the same fixed weights as set through the mean-variance optimisation over the whole sample. The market portfolio represents the capitalisation-weighted asset allocation over time. This allocation is dynamic over time on a monthly basis and always represents the market capitalisation-weighted asset allocation at the beginning of each month in time.

Second, we evaluate a stage switching model. This model has a specific and fixed asset allocation for each of the four business cycle stages. These allocations are generated per stage through mean-variance optimisation. The portfolio then switches between these allocations when the business cycle goes into a different stage. The portfolio is adjusted for the business cycle stage on a monthly basis, and all asset weights are also rebalanced at the beginning of each month to correct for gains and losses.

5.2 Results

Table 5.1 provides the results of our in-sample analysis. All strategies are compared in terms of excess return, volatility, Sharpe ratio, and asset allocation. The portfolios in this table are optimised to maximise the Share ratio and represent the optimal allocation to risky assets w^*. This allows for a straightforward comparison of asset allocations. The portfolio weights presented in Table 5.1 are averages in the case of the stage-switching portfolio for the full period, whereas the market portfolio weights are averages for all periods. The optimal mean-variance portfolios, adjusted for risk aversion, are analysed later on in Table 5.2.

We find that the stage switching portfolio outperforms both other strategies in terms of Sharpe ratio during each stage, except for the market portfolio during expansion. The stage switching portfolio benefits from the cyclical behaviour of assets by switching its asset allocation over business cycle stages. However, we find that the improvement over the full period of the stage switching portfolio to that of the fixed weight portfolio is only 0.07 in terms of the Sharpe ratio. This is low due to the fact that the stage switching portfolio optimises the Sharpe ratio per stage and not over the business cycle.

Because the stage switching model optimises Sharpe ratio per stage, it potentially increases risk systematically, and during bad times in particular. We find that the most volatile stage, expansion, is also the one with the lowest average returns. This drawback of stage switching strategies was also observed by Blitz and Van Vliet (2009), who solve this by adding constraints. We take a different approach in this paper and move from Sharpe ratio optimisations to mean-variance optimisations later on in Table 5.2. As a result, when Sharpe ratios are lowest, the strategy allocates to risk-free assets instead; lowering risk when it is least compensated for.

We find that all portfolios exhibit the same cyclical behaviour in their performance in each business cycle stage compared to the full period. During expansion and downturn, both excess returns and Sharpe ratios are low, whereas they are high during slowdown and recovery for all strategies. This confirms the findings of Blitz and Van Vliet (2009) and Jensen and Mercer (2003) that there are large differences in optimal portfolio performance that can be achieved over different stages of the business cycle.

Table 5.1

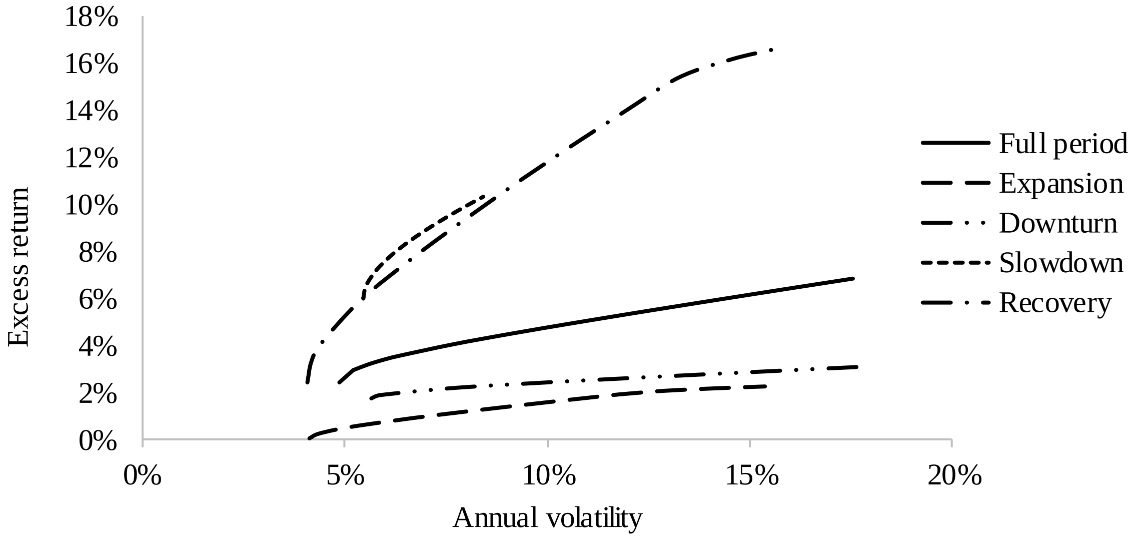
In-sample Sharpe ratio optimisations, 1973 - 2015

This table presents three different portfolios based on Sharpe ratio optimisation; the portfolio weights are the optimal allocations to risky assets. We analyse Sharpe ratio optimisations here, since they allow for straightforward comparison between different portfolios excluding the impact of risk-fee assets. Formula 5.2 is used to transform these allocation to mean-variance optimised portfolios as can be seen in table 5.2. Panel A shows the fixed weight portfolio; it has the optimal fixed assets allocation over the whole sample period. Panel B shows the switching portfolio which has a different, but fixed, allocation for each business cycle stage overtime. Panel C shows the historic market portfolio which changes as market capitalisations change overtime.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: fixed weight portfolio					
Arithmetic annual excess return (%)	0.07 ***	1.24 ***	7.18 ***	4.80 ***	3.20
Annualized volatility (%)	4.59 ***	6.07 *	6.34 **	4.86 **	5.51
Sharpe ratio	0.01	0.20	1.13	0.99	0.58
Portfolio weights (%)					
Stocks	5.32	5.32	5.32	5.32	5.32
Real estate	16.14	16.14	16.14	16.14	16.14
Bonds	77.99	77.99	77.99	77.99	77.99
Credits	0.00	0.00	0.00	0.00	0.00
Commodities	0.55	0.55	0.55	0.55	0.55
Panel B: stage switching portfolio					
Arithmetic annual excess return (%)	1.95 ***	1.88 ***	8.38 ***	11.14 ***	5.75
Annualized volatility (%)	11.88 ***	5.82 ***	6.10 ***	8.89	8.77
Sharpe ratio	0.16	0.32	1.37	1.25	0.65
Portfolio weights (%)					
Stocks	66.86	0.00	4.55	32.13	27.96
Real estate	6.91	2.70	0.00	30.79	10.42
Bonds	0.00	85.18	53.02	0.00	31.95
Credits	0.00	0.00	42.43	34.72	19.00
Commodities	26.23	12.12	0.00	2.36	10.67
Panel C: Market portolio					
Arithmetic annual excess return (%)	1.78 **	-3.51 ***	8.43 ***	10.45 ***	4.25
Annualized volatility (%)	10.58	12.37	13.41 ***	8.83 ***	11.42
Sharpe ratio	0.17	-0.28	0.63	1.18	0.37
Portfolio weights (%)					
Stocks	68.23	68.46	64.83	64.84	66.61
Real estate	0.99	0.70	0.79	0.90	0.85
Bonds	20.90	20.42	23.17	22.98	21.86
Credits	9.88	10.42	11.20	11.28	10.68
Commodities	0.00	0.00	0.00	0.00	0.00

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Figure 5.1
Efficient frontiers, full period and per stage, 1973 - 2015



The differences in portfolio performance over the business cycle are also clearly reflected in the efficient frontiers as depicted in Figure 5.1 (each individual efficient frontier and the accompanying asset allocation over the frontier can be found in Figures A5–A14 in this Chapter's appendix). We find that the efficient frontiers of the business cycle stage are very different from the average frontier over the full period. These strong differences indicate that the compensation for risk changes over the business cycle.

When we compare asset allocations in Table 5.1, we see that the optimal fixed weight portfolio of Panel A has most of its asset allocation in bonds. Bonds have the highest Sharpe ratio over the whole period (Table 4.1). As a result of the large bond allocation, we find that the fixed weight portfolio has relatively low average returns and volatilities compared to the other portfolios. The market portfolio of Panel C exhibits strong co-movements and a similar performance compared to stocks, due to their large weight in the market portfolio. The Sharpe ratio of the market portfolio is low since it does not optimally diversify its allocation, which the other portfolios do.

We find that the stage switching portfolio of Panel B has rigorously different asset allocations in the optimal portfolios of each business cycle stage. During expansion, this portfolio allocates almost only to stocks and commodities, which outperform the other assets. We see that the Sharpe ratio is very low due to all asset classes being more volatile and having low average returns. The portfolio allocates almost completely to bonds and credits during downturn and slowdown. These asset classes perform very well in terms of Sharpe ratio during these stages. This indicates that bond and credit portfolios are optimal when the economy's output is decreasing. We see a clear shift to riskier assets when economic output starts increasing again during recovery and expansion.

Table 5.2 presents the performance of the mean-variance optimised portfolios over the whole business cycle. Since the allocation to risky assets is not related to risk aversion in the mean-variance framework, we find no change in the Sharpe ratio for the fixed weight and market portfolios. Only the returns and volatilities of the market portfolio decrease as it allocates more to risk-free assets. However, when we look at the stage switching portfolio, we find large improvements in the Sharpe ratio when risk aversion increases. This is caused by the ability of the stage switching portfolio to take risk when the risk compensation is largest and to mitigate risk when compensation is lowest. When risk aversion increases from 1 to 9, we find that volatility decreases by 33%, while returns only decrease by 12%. The ability to take risk when its compensation is the highest increases the Sharpe ratio by 0.22 (or 34%) when risk aversion increases.

We conclude that a stage switching strategy outperforms strategies with fixed allocations in-sample. A strategy that switching allocations over business cycle stages optimally benefits from differences in asset classes' performance per stage. We also find that efficient frontiers largely differ over the business cycle. We conclude that the compensation for risk differs between business cycle stages. When risk aversion is included, we find that the stage switching strategy outperforms fixed allocation strategies by even larger margins; it allows for risk mitigation when compensation for it is least.

Table 5.2

In-sample mean-variance optimisations, 1973 - 2015

This table shows the average returns, volatilities and Sharpe ratio over the whole business cycle for different risk aversion levels. The allocation to risk-free assets is fixed over the whole sample period for panel A and panel C, it changes per stage for panel B. For all strategies goes that the allocations to risky assets of table 5.1 do not change; each assets retains the same weight relatively to other risky assets. Only the allocation to risky assets as a whole changes in our mean-variance framework.

Risk aversion level	1	5	9
Panel A: fixed weight portfolio			
Arithmetic annual excess return (%)	3.20	3.20	3.20
Annualized volatility	5.51	5.51	5.51
Sharpe ratio	0.58	0.58	0.58
Allocation to risk-free assets (%)	0.00	0.00	0.00
Panel B: stage switching portfolio			
Arithmetic annual excess return (%)	5.75	5.34	5.10
Annualized volatility	8.77	6.41	5.87
Sharpe ratio	0.65	0.83	0.87
Average allocation to risk-free assets (%)	0.00	20.21	32.30
Allocation during expansion (n = 144)	0.00	72.40	84.67
Allocation during downturn (n = 117)	0.00	0.00	38.26
Allocation during slowdown (n = 123)	0.00	0.00	0.00
Allocation during recovery (n = 132)	0.00	0.00	0.00
Panel C: Market portolio			
Arithmetic annual excess return (%)	4.22	2.76	1.52
Annualized volatility	11.46	7.45	4.14
Sharpe ratio	0.37	0.37	0.37
Allocation to risk-free assets (%)	0.00	34.72	63.73

5.3 Leading the business cycle

In Section 5.2, we concluded that switching between business cycle stages successfully enhances portfolio performance over fixed strategies in-sample. In Chapter 6 we use a leading indicator, the OECD CLI, to estimate the business cycle out of sample. The OECD CLI does not only track the business cycle, but tries to lead it as well. In this Section we assess if leading the business cycle adds value to portfolio optimisation.

We use the approach of Siegel (1991) to assess this. We optimise portfolios based on the same data as we did in the previous chapter, but with a one- to nine-month lead time on the business cycle to investigate how this affects excess returns. Table 5.3 presents the added value in terms of average excess returns of switching to the optimal allocation of a stage before the actual economy moves into that stage. For example: When the economy goes from expansion to downturn at period *t*, the 4-month lead strategy switches to the optimal allocation for downturn at *t-4*; 4 months before the economy actually goes into downturn. The table indicates that such switching can enhance average excess returns over all downturns from 1.74% to 4.01%. We keep the volatilities fixed with those of the concurrent analysis. This allows us to be able to assess the added value in terms of additional excess returns associated with leading the business cycle. The concurrent analysis is that of the stage-switching model in Table 5.1, which switches between stages at the same time as the business cycle does.

We find that leading the business cycle significantly enhances returns for both expansion and recovery. For expansion, any lead improves performance, while longer leads improve it most. For recoveries, a lead time of 3 to 6 months appears optimal. It is difficult to draw statistically significant conclusions over leading downturns; however, we see that leading by 4 months or longer provides economically large and partially significant additional excess returns. Leading slowdown, however, decreases excess returns earned during that stage. This can be explained by the optimal allocation during the stage. During the switch from downturn to slowdown, the optimal portfolio allocates a large part (42%, as found in Table 5.1) to credits. When we look at Table 4.1, we find that credits perform poorly during downturn (-2.51% excess return). This causes the switch to credits during downturn to reduce returns instead of enhancing them. When we combine these findings over the full-period, we find that leading the business cycle by 2 to 5 months provides both statistically significant and economically large additional excess returns confirming the findings of Siegel (1991).

Table 5.3

Added value of leading the business cycle, in %, 1973 - 2015

This table shows additional average annualized excess returns that are realised when leading the business cycle by a specified number of months. An x-month lead on a stage means that the asset allocation of a portflio switches to the optimal asset allocation of that stage x months before the economy goes into that stage. Both volatilities and allocations are kept fixed at the optimal concurrent allocation. These are the allocation and volatilities of the stage switching optimisation of table 5.1 panel B.

	Expansion	Downturn	Slowdown	Recovery	Full period
Concurrent	1.89	1.74	8.38	11.14	5.29
1-month lead	3.50 **	0.18	8.42	12.26 *	5.65
2-month lead	7.11 ***	0.09	7.34 *	12.26 *	6.36 ***
3-month lead	5.98 ***	0.12	5.38 ***	15.46 ***	6.36 ***
4-month lead	5.69 ***	4.01 **	3.95 ***	14.80 ***	6.71 ***
5-month lead	5.56 ***	3.30	3.23 ***	15.00 ***	6.38 ***
6-month lead	4.58 ***	3.54 *	2.49 ***	15.02 ***	5.99 *
7-month lead	7.49 ***	3.47	0.97 ***	12.54 **	5.77
8-month lead	8.06 ***	1.58	0.19 ***	12.19 *	5.20
9-month lead	8.34 ***	4.17 **	0.68 ***	9.69 **	5.39
Annualized volatility (%)	11.88 ***	5.82 ***	6.10 ***	8.89	8.77

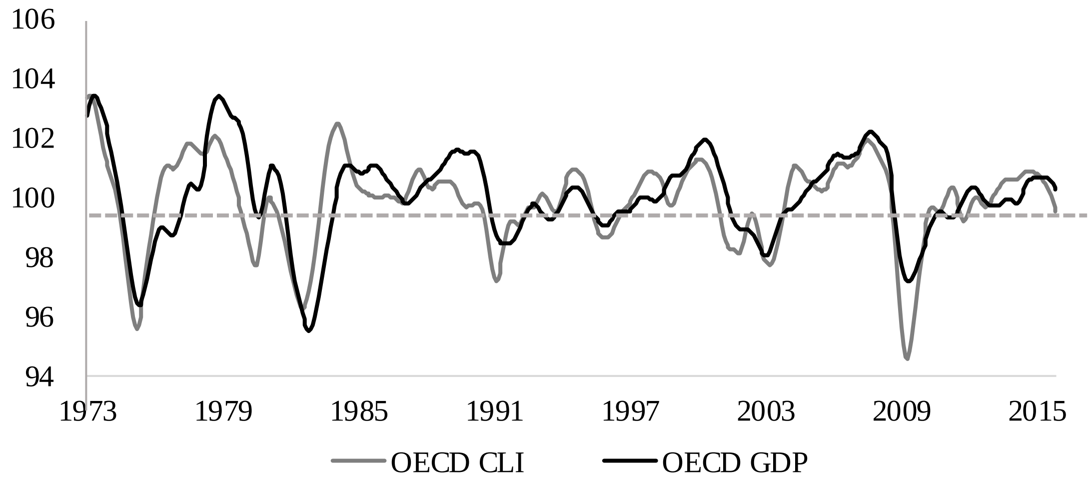
***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

5.4 Business cycle prediction

In Sections 5.2 and 5.3, we have concluded that both switching between optimal asset allocations over the business cycle and leading the business cycle add value to portfolio optimisation. In Chapter 6 we use a leading indicator, the OECD CLI, to estimate the business cycle out of sample. In this Section we assess how well the OECD CLI tracks the business cycle in-sample, and if it is able to lead the business cycle.

The OECD CLI aims for a lead time of six to nine months on the business cycle (OECD, 2016). It is published with a delay of two months due to data availability. This delay results in an estimated actual lead time on the economy of four to seven months. A comparison of the OECD GDP and OECD CLI can be found in Figure 5.2. Indicators switch between stages when their values change direction (decreasing versus increasing) or when they cross the trend (100) as discussed in Section 3.4. It is difficult to quantify the lead time of the OECD CLI over the OECD GDP since it is dynamic over time. However, when we analyse Figure 6.1, we see that in most cases changes in the direction of the OECD GDP are preceded by those of the OECD CLI. Furthermore, the OECD CLI consistently crosses the trend before the OECD GDP does. The OECD CLI appears to lead the OECD GDP graphically.

Figure 5.2
OECD indicators, trend = 100, 1973 - 2015
The OECD CLI is adjusted for its two month publication delay



In Table 5.4 we assess the performance of the OECD CLI as a business cycle indicator in Panel B. We use the methodology of the stage switching strategy of Section 5.1, but base business cycle stages on the OECD CLI instead of the OECD GDP. We optimise the portfolios in Table 5.4 to maximise Sharpe ratios to allow for straightforward comparison of asset allocations.

When we compare the stage switching portfolio of Panel B with the (optimal) fixed weight portfolio of Panel A, we find that the stage switching portfolio improves performance for every stage in terms of Sharpe ratios. The stage switching portfolio does this by allocating more aggressively to risky asset classes during expansions, downturns and recoveries, and allocating completely to bonds during slowdown. Over the whole time period, the Sharpe ratio increases from 0.58 to 0.73 without adjusting for risk aversion. We conclude that the OECD CLI can be used as a business cycle indicator to outperform strategies with fixed asset allocations in-sample.

When comparing the switching strategies, we find that the OECD CLI of Panel B outperforms OECD GDP of Panel C as a business cycle indicator during expansion, downturn and recovery. We find that the OECD CLI-based portfolio increases average excess returns during these periods, while volatilities are comparable. We do find that the OECD CLI classifies more periods as expansions instead of recoveries. Performance is worst during expansion and best during Recovery. While this could partially drive the portfolio performance differences, we find that the portfolio performance increases over the whole cycle in terms of Sharpe ratio.

When we compare the asset weights of the two switching strategies, they first appear largely different. However, in Chapter 4, we found that stocks and real estate behave comparably over the business cycle; the same goes for bonds and credits. We combine the asset weights of these asset classes in Table A2 (Appendix – Chapter 5). We now find that asset allocations are at least 70% identical per stage and 80% identical on average for all stages. The average full period allocation is even 90% comparable. We, therefore, have confidence in the use of the OECD CLI as a business predictor for the OECD CLI portfolio in further analyses.

Table 5.4

Business cycle measurement and prediction, Sharpe ratio optimisations, 1973 - 2015

Panel A presents the fixed weight portfolio; this is the optimal assets allocation over the whole period. Panel B presents the switching portfolio which has a different, allocation for each business cycle stage overtime based on OECD CLI predictions. Panel C presents the stage switching portfolio based on the actual OECD GDP business cycle of tabel 5.1. It is important to keep in mind that Panel B and Panel C label months differently, this means that their stages do not necessarily coincide Note: The allocation and performance of the fixed weight strategy of Panel A is the same as in table 5.1. However, each month is labelled based on the OECD CLI. This results in a different performance per stage when compared to the same strategy of table 5.1.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: fixed weight portfolio					
Arithmetic annual excess return (%)	0.16 ***	3.79	4.88 ***	5.71 ***	3.20
Annualized volatility	4.58 ***	5.18	7.11 ***	5.03	5.51
Sharpe ratio	0.03	0.73	0.69	1.14	0.58
Portfolio weights (%)					
Stocks	5.32	5.32	5.32	5.32	5.32
Real Estate	16.14	16.14	16.14	16.14	16.14
Bonds	77.99	77.99	77.99	77.99	77.99
Credits	0.00	0.00	0.00	0.00	0.00
Commodities	0.55	0.55	0.55	0.55	0.55
Panel B: Stage switching portfolio, OECD CLI based					
Arithmetic annual excess return (%)	4.39 ***	4.57 ***	6.70	15.90 ***	7.01
Annualized volatility	13.58 ***	5.92 ***	6.34 ***	8.28 *	9.56
Sharpe ratio	0.32	0.77	1.06	1.92	0.73
# Observations	166	137	118	95	516
Portfolio weights (%)					
Stocks	0.00	0.28	0.00	30.19	5.49
Real Estate	43.74	29.28	0.00	41.24	28.68
Bonds	0.00	65.73	100.00	0.00	41.84
Credits	0.00	0.00	0.00	19.31	3.46
Commodities	56.26	4.70	0.00	9.25	20.53
Panel C: Stage switching portfolio, OECD GDP based					
Arithmetic annual excess return (%)	1.95 ***	1.88 ***	8.38 ***	11.14 ***	5.75
Annualized volatility	11.88 ***	5.82 ***	6.10 ***	8.89	8.77
Sharpe ratio	0.16	0.32	1.37	1.25	0.65
# Observations	144	117	123	132	516
Portfolio weights (%)					
Stocks	66.86	0.00	4.55	32.13	27.96
Real Estate	6.91	2.70	0.00	30.79	10.42
Bonds	0.00	85.18	53.02	0.00	31.95
Credits	0.00	0.00	42.43	34.72	19.00
Commodities	26.23	12.12	0.00	2.36	10.67

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

When we compare the allocations in more detail, we find that the OECD CLI portfolio allocates more to commodities during expansions and more to real estate during downturns. We expect this to be driven by the lead time of the OECD CLI on the business cycle. The literature found stock market prices to decrease before downturns took place (Siegel, 1991). We find that leading the business cycle makes holding stocks during expansion more profitable. Leading the business cycle potentially allows selling those stocks before stock market prices decrease. This is something we also observe in Table 5.3. Since the portfolio performance of the OECD CLI is higher than that of the OECD GDP, we find the latter explanation to be more likely.

We conclude that the OECD CLI captures the cyclical behaviour of average asset returns; it significantly enhances performance of a fixed-weight strategy by changing asset allocation over the business. We find that the asset allocations of the OECD CLI are comparable to those of the OECD GDP when allocations to stocks and real estate, and bonds and credits are combined. We are, therefore, confident in the use of the OECD CLI as a business cycle predictor. We find that the OECD CLI outperforms the actual OECD GDP as a business cycle indicator. This outperformance is explained by the lead the OECD CLI appears to have on the actual business cycle, which we find to add value to portfolio performance.

Chapter 6

Out-of-sample analysis

We find three phenomena that add value to portfolio optimisation when anticipated based on the in-sample analyses in Chapters 4 and 5. First, during each business cycle stage different asset classes perform best in terms of both risk and return. Second, we find that the compensation for risk differs per stage over the business cycle. Third, we find that leading the business cycle as a whole adds value to portfolio performance. We perform an out-of-sample analysis in this chapter to assess whether these findings can be used to enhance portfolio performance in practice.

In Chapter 5, we assumed the business cycle stages, average excess returns, volatilities and correlations to be known ex ante when optimising portfolios. For our out-of-sample analysis, we assume that these variables are all unknown and have to be estimated.

In Section 6.1, we extend our stage switching model in an out-of-sample framework, in which the model uses only ex-ante information. We find several drawbacks to the use of the stage switching model, we fix several drawbacks by using a Black-Litterman model in Section 6.2. Section 6.3 compares our out-sample portfolios with each other and with the in-sample models of chapter 5.

6.1 Out-of-sample stage switching model

6.1.1 Methodology

In Chapter 5, we used a stage switching model to optimise in-sample portfolios. In this section we follow the same approach out of sample, again based on the mean-variance utility function of Formula (5.1). We extend the stage switching model to be able to use it in an out-of-sample framework. Instead of only one optimisation, we adjust our model to create multiple ex-ante optimisations in a rolling-window approach. This model starts after a specific period of time we call $T_{i.}$ The period $[1;T_i]$ forms the input of the model. The model uses a mean-variance approach to estimate the optimal allocation for next month $T_{i\ +1}$ based on the variance-covariance matrix and expected returns as derived from the input period $[1;T_i]$. Similarly to the stage switching portfolio, our model creates an allocation depending on the corresponding business cycle stage. This means that for each period of time, four covariance matrices and return vectors are estimated (one for each business cycle stage). Which of these four matrices and four vectors are used for the mean-variance optimisation is determined by the OECD CLI business-stage prediction for that period in time. The optimal allocation to risky assets w^* is saved for each period that is estimated. We then move to the next period and add the actual data of the month T_{i+1} to the inputs. The input of the model that is used for the next estimation T_{i+2} is then $[1;T_{i+1}]$. This means that the amount of observation increases over time after each estimation. We repeat this process for the whole time series up to December 2015. Through this model, we generate a vector with the optimal asset allocation for each period in time, excluding the initial input period. Finally, our model adjusts these portfolios for different risk-aversion levels. We start our analysis after the first business cycle; the first estimate is based on 70 data points and that a total of 446 periods are estimated.

A few additions to this model are necessary to allow for its practical use. In the beginning of our sample, we find some periods with negative expected returns for all asset classes; during these periods, the investment strategy is not to invest in risky assets at all. Furthermore, we discussed in Section 2.1 that the OECD CLI is prone to revisions over time as new data become available. This means that we cannot use the most recent data for the OECD CLI over the whole time series. These data could be fitted to the actual historical GDP data ex post and are, therefore, unusable in an out-of-sample analysis. To adjust for this, we use the historic OECD CLI series since its inception; each period we estimate has its own historic time series that was available at that time. This means that the OECD CLI used for a mean-variance optimisation reflects the actual available data at the moment of making that investment decision. Revisions are only included in estimations historically, if they were actually known at that period in time.

6.1.2 Results

Table 6.1 compares the performance of the out-of-sample approach with that of the in-sample approach to the stage switching portfolio based on the OECD CLI. The strategies are compared in terms of the Sharpe ratio to allow for a comparison of the allocations to risky assets. The allocation to risk-free assets during expansions for the out-of-sample model is an exception; the model to risk-free assets when the expected returns of all assets are negative.

Table 6.1

Stage switching strategy portfolio performance, Sharpe ratio optimised, 1978 - 2015

This table compares the out-of-sample and in-sample performances of our stage switching portfolio based on the OECD CLI. This table is optimised to maximize the Sharpe ratio; it shows to optimal allocation to risky assets only. There is one exception: the out-of-sample portfolio of Panel A allocates to risk-free assets when the expected returns of all asset classes are negative. The in-sample portfolio performance of panel B differs from table 5.4 due to different time periods compared. This is caused by the need of an estimation window in the out-of-sample analysis. The mechanics of behind the in-sample portfolio remain the same.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: Out-of-sample stage switching portfolio, OECD CLI based					
Arithmetic annual excess return (%)	10.92	8.77 *	6.99 ***	17.57 ***	10.53
Annualized standard deviation (%)	16.72 ***	9.71 ***	6.29 ***	8.89 ***	11.67
Sharpe ratio	0.65	0.90	1.11	1.98	0.90
Allocation to risk-free assets (%)	15.00	0.00	0.00	0.00	4.71
Average portfolio weights (%)					
Stocks	12.64	4.08	3.04	43.09	13.51
Real Estate	8.79	48.62	0.49	42.33	23.01
Bonds	0.00	18.66	95.93	5.93	29.75
Credits	0.00	0.00	0.29	5.07	0.98
Commodities	63.56	28.64	0.25	3.58	28.04
Panel B: In-sample stage switching portfolio, OECD CLI based					
Arithmetic annual excess return (%)	6.16 **	5.16 ***	6.85 *	19.07 ***	8.35
Annualized volatility	12.88 ***	5.67 ***	6.52 ***	9.49	9.38
Sharpe ratio	0.48	0.91	1.05	2.01	0.89
Portfolio weights (%)					
Stocks	40.99	9.59	0.00	40.27	22.56
Real Estate	47.22	20.99	0.00	49.09	29.04
Bonds	0.00	69.42	95.64	0.00	41.70
Credits	0.00	0.00	4.36	0.30	1.14
Commodities	11.79	0.00	0.00	10.34	5.56

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Table 6.1 indicates that the out-of-sample model has a comparable Sharpe ratio over the whole period, but with a higher level of average excess return and volatility. This is mainly driven by the expansion and downturn stages, when both risk and return are increased. We find that the asset allocations of the portfolios, and therefore the performances, are remarkably similar during slowdown and recovery. Regardless of these differences, we find that the Sharpe ratios are comparable and move in a similar way over the business cycle. We find that the out-of-sample approach successfully captures the potential of business cycle based portfolio optimisation that we find in sample.

When we look into the differences during expansion and downturn, we find the out-of-sample portfolio to allocate more to commodities. This is driven by the strong performance of commodities in the beginning of our sample. More recently, their performance has been negative (Table 4.3). This reduces the allocation to commodities over the full period for the in-sample portfolio, while the largest part of the out-of-sample portfolio is not influenced.

In Table 6.2, we optimise the out-of-sample model for the mean-variance utility function represented by Formula (5.1). The allocation amongst risky assets of Table 6.1 (Panel A) does not change when we optimise for the mean-variance utility function, only the allocation to risky assets as a whole changes. We find that the Sharpe ratios increase for higher levels of risk aversion. This is mainly driven by the increases in allocation to risk-free assets during expansion. Allocating dynamically to risk-free assets, allows to mitigate risk when the compensation for it is least, which is mainly during slowdown and recovery. We find that the out-of-sample portfolio successfully adapts to differences in compensation for risk that we observed in Section 5.2 in a mean-variance utility framework.

Table 6.2

Stage switching strategy performance, mean-variance optimised, 1978 - 2015

This table looks at the out-of-sample stage switching portfolio only. It shows the average returns, volatilities and Sharpe ratio over the whole business cycle for different risk aversion levels in a mean-variance utility framework. The allocation to risky assets of table 6.1 panel A does not change; each assets retains the same weight relatively to other risky assets. Only the allocation to risky assets as a whole changes in our mean-variance framework.

	Expansion	Downturn	Slowdown	Recovery	Full period
			Risk aversion level of 1		
Arithmetic annual excess return (%)	11.53	8.77 **	6.99 ***	17.57 ***	10.72
Annualized standard deviation (%)	15.88 ***	9.71 **	6.29 ***	8.89 ***	11.30
Sharpe ratio	0.73	0.90	1.11	1.98	0.95
Allocation to risk-free assets (%)	17.55	0.00	0.00	0.00	5.51
			Risk aversion level of 5		
Arithmetic annual excess return (%)	9.90	8.81 *	6.99 ***	17.57 ***	10.22
Annualized standard deviation (%)	11.97 ***	9.56	6.29 ***	8.89	9.64
Sharpe ratio	0.83	0.92	1.11	1.98	1.06
Allocation to risk-free assets (%)	40.66	1.15	0.00	0.00	13.06
			Risk aversion level of 9		
Arithmetic annual excess return (%)	7.16 **	7.78 **	6.99 ***	17.57 ***	9.08
Annualized standard deviation (%)	9.02 *	7.75	6.29 ***	8.89	8.10
Sharpe ratio	0.79	1.00	1.11	1.98	1.12
Allocation to risk-free assets (%)	54.69	16.77	0.00	0.00	21.49

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

6.1.3 Limitations

The stage switching model has some limitations in its methodology. The model uses basic mean-variance optimisation, which is extremely sensitive to small changes in inputs or errors in the estimations of its inputs (Bekkers, Doeswijk, & lam, 2009). This is clearly observed in the assets allocations of the stage switching model presented in Tables 6.1, in which every stage has a rigorously different allocation from the other stages.

Related to this, the model makes its first estimates based on a very low number of input data *n*. This leaves a large room for errors in the estimations. The total *n* for the first estimation equals 70 for the first estimation, however, we pool these into sub-datasets for each business cycle stage to estimate return vectors and variance-covariance matrices for each business cycle stage. The resulting vectors and matrices for slowdown and recovery for the first estimate are based on an *n* of only 11.

Figures A16, A17, A18 and A19 in this chapter's appendix illustrate the expected excess return estimates based on the number of months on which they are estimated. We find that, especially during slowdown and recovery (Figures A18 and A19), expected return estimates are volatile when based on a low number of observations. In general, estimates become more stable when n reaches the area between 40 and 60 observations. A solution could be to simply increase our input time series and to decrease the amount of estimates as a consequence. We find that the number of estimates is reduced from 446 to 298 for a minimum n of 40 or to 240 for a minimum n of 60. The number of estimated business cycles decreases from five, of which one is an incomplete cycle, to just three, of which two are incomplete cycles. The large reduction in the number of estimates and business cycles is undesirable since the conclusions of the analysis become less informative.

6.2 Out-of-sample Black-Litterman model

The stage switching model has two main drawbacks. The sensitivity of asset allocations to estimated inputs, and the small number of input data in the beginning of our estimation window. In this section, we resolve both problems by applying a Black-Litterman model. We extend this model to allow for time-varying portfolio optimisation and to adjust for the number of observations used in its estimations.

The Black-Litterman model resolves the sensitivity issues by starting from an equilibrium allocation, which is the market portfolio in this study. This means that without views, or confidence in those views, the strategy invests according to the market portfolio. This results in a more balanced portfolio overtime, less extreme allocations, and more intuitive portfolios (Drobetz, 2001). This also makes the portfolio also less prone to estimation errors and corner solutions; it follows the direction of the market as an aggregate.

We extend the Black-Litterman model to solve for the small number of input data early on in our sample. As a result, the model adjusts for the number of input data on which estimates are based. This means that the impact of estimates is dynamic over time; the impact increases when estimates are based on more data.

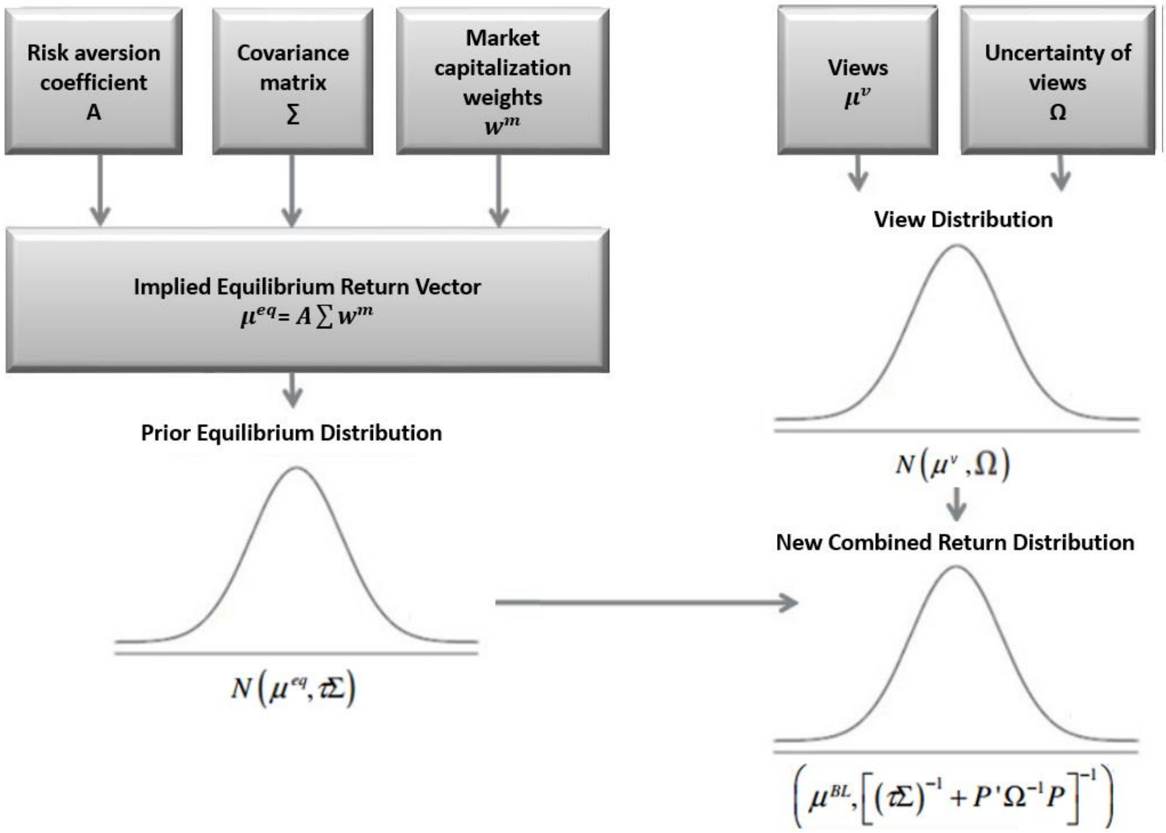
6.2.1 Methodology

We first introduce the general concept of the Black-Litterman model, then elaborate on the inputs of each parameter, and finally explain the extension on this model to allow for out-of-sample use. The model is named after the researchers Black and Litterman who introduced it in 1992. We follow the approach to this model as lined out by Baele (2016) in the Financial Analysis and Investor Behaviour 2015–2016 course of the MSc in Finance program at Tilburg University. This approach is graphically presented in Figure 6.1.

The Black-Litterman model allows investors to combine their personal views with an equilibrium view (the market portfolio in this study). The equilibrium provides a neutral reference point on the investment universe and forms the basis of the Black-Litterman model. This reference point is then expanded by both the views of an investor and the confidence in those views. The Black-Litterman model optimises the same mean-variance utility function of the basic mean-variance approach (Formula (5.1)).

Figure 6.1

The Black-Litterman approach to portfolio optimization



Adapted from "The Black-Litterman Approach to Global Asset Allocation" by Baele (2016)

First, we determine the return distribution in the equilibrium that represents the views of the market. We follow Baele (2016) and use the implied returns of the market portfolio as equilibrium returns. This means that we reverse-engineer the market portfolio into implied returns. To do so, we convert the first-order condition of the mean-variance utility function of Formula (5.1), namely Formula (5.2), into Formula (6.1). Instead of using expected returns as inputs to calculate the optimal weights, we use the market weights as input to calculate the implied expected excess returns of the market.

$$\mu^{eq} = A \sum w^* \tag{6.1}$$

Besides the market weights, we need to estimate the variance-covariance matrix $\sum$ of our assets and a risk-aversion coefficient A to be able to reverse-engineer the equilibrium return vector. Similarly to the previous chapters, we do not pick a specific risk-aversion coefficient but analyse for coefficients 1, 5, and 9.

We estimate our variance-covariance matrix based on data over the complete sample period. We realise that this means that we base this parameter on ex-post data, but believe that this does not substantially influence our model because of two reasons. First, after a brief comparison of the underlying correlations between asset classes we find that they are fairly stable over time. This comparison can be found in Figures A20 - A23 in this chapter's appendix. Second, the model allocates mainly to the market portfolio in the beginning of our sample period. The estimated correlation coefficients change most during that period, but the impact of them through variance-covariance matrix (measured through tau) is the least.

We calculate the equilibrium returns and their distribution N~($\mu^{eq}, \tau \sum$) based on the three previously discussed inputs. Tau (or τ) stands for the maximum percentage of predictable information in returns in this distribution. The higher the value for tau, the larger the expected uncertainty of the equilibrium returns becomes. This allows for larger deviations from the equilibrium and thus a larger impact of the investors views on the Black-Litterman asset allocation. A tau of 0% leads to an asset allocation identical to the equilibrium allocation. In this study we increase tau overtime to allow for a larger impact of our views on the optimal asset allocation as calculated through the model. This approach results in a higher impact of business cycle based views when the number of data points supporting those views increases. We derive tau later in this section.

Next to the equilibrium distribution, we formulate the distribution of our views. We use historic data to estimate the cyclical behaviour of asset returns and volatilities in our sample. We first determine the expected return vector μ^{v}, which is the rolling sample mean of the historic excess returns. Besides the expected return vector, we calculate **Ω**, which is a diagonal matrix that represents the variance of the estimated expected returns. The matrix **Ω** is estimated by the historic volatilities for the assets in the vector μ^{v}. Both μ^{v} and **Ω** are estimated for the specific business cycle stage that is predicted by the OECD CLI at that moment in time, using only historic data from that same stage. These factors lead to the following return distribution of our views N~(μ^{v}, Ω).

For each period in time *t*, the average excess returns and volatilities are calculated only based on data that were available at that period of time in the past. The period [$1;T_i$] is again the input period of the model, which is expanded for each month that passes in a rolling-window approach. We estimate the expected excess returns and volatilities of each asset based on the corresponding business cycle stage as predicted by the historic OECD CLI data as was known at each period in time *t*. This approach is equal to that of the stage switching model of Section 6.1.1.

We opt for the use of a diagonal matrix for Ω to reduce the amount of parameters that have to be estimated; only variances are included, and covariances are not taken into account. Another argument for this approach is our findings of Chapter 4 that indicate that returns and variances change over the business cycle, and we cannot conclude that correlations exhibit similar behaviour. We, therefore, do not estimate their impact within our views.

The Black-Litterman model combines the equilibrium and views distributions into one single distribution with the following properties $N\sim(\mu^{bl}, \left[\, (\tau \sum)^{-1} + \Omega^{-1} \,\right]^{-1}$. The Black-Litterman model's expected return vector μ^{bl} is calculated through Formula (6.2). Formula (6.3) is used to calculate unrestricted asset weights w^{bl}. The restriction on short selling and requirement of fully investing all wealth in the tangency portfolio is also applied here (Formulae (5.3) and (5.4)). We achieve the optimal restricted asset allocation through the mean-variance optimisation of the utility function of Formula (5.1) by changing the asset weights of Formula (6.3) subject to restrictions (5.3) and (5.4)

$$\mu^{bl} = \left[\, (\tau \textstyle\sum)^{-1} + \Omega^{-1} \,\right]^{-1} \left[\, (\tau \textstyle\sum)^{-1} \mu^{e} + \Omega^{-1} \mu^{v} \,\right] \tag{6.2}$$

$$w^{bl} = A^{-1} \textstyle\sum^{-1} \mu^{bl} \tag{6.3}$$

The last parameter we have to choose is tau. To come to a clear estimate of tau we Formula (6.4) of Formula (6.2), which we can do if we assume that Ω equals ∑. This is clearly the case in this study since Ω is business cycle dependent and ∑ is not. However, we still follow this approach to be able to illustrate the role of tau in the model. In Formula (6.4) we observe that tau denotes the impact of the return vector of our views. When $\tau = 1$, we find that the average excess return vector of our views has an equal impact compared to the average excess return vector of the equilibrium.

$$\mu^{bl} = [\mu^{e} + \tau\mu^{v}] \quad [1 + \tau]^{-1} \tag{6.4}$$

We extend the Black-Litterman model of Baele (2016) to allow for a dynamic tau. We make tau dependent on the number of observations that is used for the estimation of our views. This solves the estimation issue in the beginning of our sample when the number of observations is low. The impact of the views derived from these observations is thus also low through tau, while it increases as estimates are based on more observations. We extend the model by using Formula (6.6) to calculate tau. Here, n_0 is a constant value that can be set to the needs of the user and n_t is the number of observations that is used to derive views at time period t. For every period in our rolling-window approach we estimate a new value for tau.

$$\tau_t = n_t \,/\, n_0 \tag{6.6}$$

In this study, we use a value of 293 for n_0. If we then base our estimates on $n_t = 293$ observations, we find that the estimation for each specific stage is based on at least 60 observations. When we have over 60 observations per stage ($n > 293$ and $\tau > 1$), we are confident to put more weight on our views than on the equilibrium. Figures A20-A23 in this chapter's appendix illustrate that the estimates for the average expected excess returns per stage are fairly stable after an n of 60. Reaching 60 observations per stage requires more than $60 \times 4 = 240$ observations, since not each stage occurs with the same frequency (table 4.1). We present a sensitivity analysis on other values of n_0 later on.

We run this Black-Litterman model in a rolling-window approach comparable to that used for the stage switching model in Section 6.1; we run the model for each period in time in our sample after the input period [$1;T_i$]. We calculate the optimal asset allocation according the Black-Litterman model for each period in time after T_i based on the data that was available at that moment in time. The input period is again 70 months, which is equal to that of the stage switching model. While using an input period is not necessary for the Black-Litterman approach, we do so to be able to directly compare the output to that of chapter 6.1. Each optimisation uses the corresponding market portfolio weights and views in terms of excepted returns and volatilities based on the corresponding OECD CLI stage. Tau is recalculated for each estimation. The resulting w^{bl} for each period in time are then used to calculate the actual historic returns.

6.2.2 Results

In this section we compare the portfolio performance and asset allocation of the Black-Litterman model with the in-sample stage switching portfolio. Table 6.3 compares the Black-Litterman models with risk aversion levels of 1 and 5 to the in-sample stage switching portfolio. We leave the portfolio with a risk aversion level of 9 to this chapter's appendix (Table A3) to be able to compare the other portfolios on one page. A brief comparison finds that the portfolio with A = 9 has a 89% similar asset allocation over the business cycle when compared to the portfolio with A = 5. As a result, the performances of both portfolios are also comparable over the business cycle. The in-sample stage switching portfolio of Table 6.3 is Sharpe ratio optimised; it shows the optimal allocation to risky assets in-sample. This makes comparisons easier as the Black-Litterman model only invests in risky assets.

While we conclude that the portfolios with risk aversion levels of 5 and 9 are very comparable, we also find that the portfolios with risk aversion levels of 1 and 5 differ much more in terms of asset allocations. Risk aversion has a large impact on the Black-Litterman model estimates. This is caused by the role risk aversion has in the model; a higher level of risk aversion increases the weight that is put on the equilibrium instead of the views. We do find that the Sharpe ratios of both portfolios are comparable. This indicates that risk aversion is important for determining the asset allocation, returns and riskiness of a portfolio, but that the model performs consistently well over different levels of risk aversion. Noteworthy is that we find the volatility to stabilise over the business cycle stages for the risk aversion level of 5.

In general, we find that the average portfolio for a higher level of risk aversion is more closely related to that of the equilibrium. More specifically, we find that an increase in risk aversion tilts the asset allocations from commodities to bonds during expansion and downturn. The large allocation to commodities is driven by the asset class' strong performance early on in our sample period, this large allocation is also observed for the stage switching model in Section 6.1. We find that the tilt from commodities to bonds decreases volatility and average returns, while keeping Sharpe ratios similar. We also find a switch from real estate to stocks during downturn and recovery. As we found in Chapter 4, these assets have a comparable profile over the business cycle, however, stocks offer a lower average return against a lower volatility. We find this to decrease the very high Sharpe ratio during recovery from 2.17 to 1.97. These differences in allocation result in a comparable Sharpe ratio over the whole period. As a result of the increase in risk aversion, we find that volatilities and with them average excess returns to decrease.

When we compare the Black-Litterman portfolio with a risk aversion level of 5 (panel B) to the in-sample stage switching portfolio (panel C), we find clear differences in allocations. Due to the use of an equilibrium portfolio, which is the market portfolio with a large allocation to stocks, we find the Black-Litterman model to structurally invest more in stocks. During

Table 6.3

Black-Litterman out-of-sample portfolio performance, 1978 - 2015

This table compares the out-of-sample Black-Litterman model with the in-sample performances of our stage switching portfolio based on the OECD CLI. The OECD CLI is optimised to maximise the Sharpe ratio; it shows to optimal allocation to risky assets . The Black-Litterman model is optimised for mean-variance utility but always allocates to risky assets only by design. The Black-Litterman performance for risk aversion level 9 can be found in table A3 in this chapter's appendix.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: Out-of-sample Black-Litterman model, Risk aversion level of 1, n_o = 293					
Arithmetic annual excess return (%)	11.46	8.51 ***	6.97 ***	24.86 ***	11.83
Annualized standard deviation (%)	15.44 ***	11.80	9.11 ***	11.48	12.51
Sharpe ratio	0.74	0.72	0.77	2.17	0.95
Average portfolio weights (%)					
Stocks	15.46	8.69	16.31	49.70	20.07
Real estate	2.00	37.67	0.08	50.30	19.38
Bonds	21.84	3.59	0.73	0.00	7.96
Credits	0.00	7.68	82.87	0.00	22.60
Commodities	60.71	42.38	0.00	0.00	29.98
Panel B: Out-of-sample Black-Litterman model, Risk aversion level of 5, n_o = 293					
Arithmetic annual excess return (%)	6.20 ***	7.39 ***	5.55 ***	20.30 ***	8.76
Annualized standard deviation (%)	9.10	9.33	9.08	10.32	9.46
Sharpe ratio	0.68	0.79	0.61	1.97	0.93
Average portfolio weights (%)					
Stocks	19.99	37.82	26.79	67.68	34.83
Real estate	2.88	15.56	0.01	30.16	10.33
Bonds	51.16	27.06	6.21	0.00	24.58
Credits	0.00	0.19	66.99	2.16	17.11
Commodities	25.98	19.37	0.00	0.01	13.15
Panel C: In-sample stage switching portfolio, OECD CLI based					
Arithmetic annual excess return (%)	6.16 **	5.16 ***	6.85 *	19.07 ***	8.35
Annualized volatility	12.88 ***	5.67 ***	6.52 ***	9.49	9.38
Sharpe ratio	0.48	0.91	1.05	2.01	0.89
Portfolio weights (%)					
Stocks	40.99	9.59	0.00	40.27	22.56
Real Estate	47.22	20.99	0.00	49.09	29.04
Bonds	0.00	69.42	95.64	0.00	41.70
Credits	0.00	0.00	4.36	0.30	1.14
Commodities	11.79	0.00	0.00	10.34	5.56

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

recovery, this is largely at the cost of real estate, and during downturn at the cost of both bonds and real estate. We also find a strong allocation to commodities during expansion and downturn, which we also observed in the out-of-sample stage switching portfolio. This is caused by the large differences in the performance of commodities over time. The allocation to commodities also drives the large allocation to bonds, these asset classes have a negative correlation of -0.019 with commodities during expansion as we found in table 4.2. Furthermore, bonds have the lowest volatility of all asset classes, which decreases average volatility the most when combined with the high volatility of commodities.

While allocations differ, we conclude that the Black-Litterman model successfully captures the in-sample potential of business cycle based portfolio optimisation. Sharpe ratios over the whole period are comparable; while we find differences per stage, we observe the same trend of relatively high Sharpe ratios during recovery and much lower Sharpe ratios during the other stages.

6.2.3 Sensitivity

In our analysis we have used $n_0 = 293$. Tau is determined by n_0 (Formula 6.6), and determines the weight that is put on business cycle views compared to the equilibrium. As a result, a lower n_0 makes the impact of our views larger in total, and larger more early on in the rolling window. On the other hand, we see that the impact of our views is driven by the level of risk aversion *A*. A higher level of risk aversion results in a larger weight on the equilibrium. Table 6.4 presents the sensitivity of the average excess return, volatility and Sharpe ratio over the full sample to these inputs.

We find that risk-aversion levels have a much larger impact on the Black-Litterman model performance than the different inputs for n_0. The most aggressive approach, with a low level of risk aversion and a low n_0 has the highest returns, but also the highest volatility. Aggressive investors can earn higher returns at the price of a higher volatility by putting more weight on the business cycle views. A more conservative approach to either one of the inputs improves Sharpe ratio from that point. Being conservative on both measures decreases performance in terms of Sharpe ratio.

Table 6.4

Black-Litterman out-of-sample sensitivity analysis, 1978 - 2015

	Risk aversion level		
	1	5	9
Tau based on n_o = 147	11.85	9.14	7.75
Arithmetic annual excess return (%)	13.07	9.51	7.84
Annualized standard deviation (%)	0.91	0.96	0.99
Sharpe ratio			
Tau based on n_o = 293			
Arithmetic annual excess return (%)	11.83	8.76	7.29
Annualized standard deviation (%)	12.51	9.46	8.10
Sharpe ratio	0.95	0.93	0.90
Tau based on n_o = 440			
Arithmetic annual excess return (%)	11.77	8.42	6.99
Annualized standard deviation (%)	12.17	9.52	8.40
Sharpe ratio	0.97	0.89	0.83
Tau based on $n_o = 586$			
Arithmetic annual excess return (%)	11.57	8.16	6.79
Annualized standard deviation (%)	11.96	9.61	8.66
Sharpe ratio	0.97	0.85	0.78

6.3 Portfolio performance compared

6.3.1 Out-of-sample portfolios

In Table 6.5, we compare the performance and asset allocations of both out-of-sample models. Asset weights for stocks and real estate are combined to allow for a straightforward comparison; we take the same approach for bonds and credits. The allocations per asset class per strategy have not changed and can be found in Tables 6.1 and 6.3. The Black-Litterman model only invests in risky assets, whereas the stage switching model is able to invest in risk-free assets. This makes a large impact only during expansions.

The stage switching model outperforms the Black-Litterman model for each period, and over the whole time period in terms of Sharpe ratio. Over the full period, we find that volatilities are comparable while the average excess return of the Stage switching model is larger. The difference in performance is largest during slowdown. This is caused by the allocation to stocks of the Black-Litterman model; stocks perform badly during slowdown (Table 4.1). Furthermore, we find a larger role for commodities in the stage switching portfolio. This is driven by their strong performance early on in the sample. The Black-Litterman model only has a limited impact of views at that period in time, this results in a much smaller allocation to commodities. The small allocation to commodities in the Black-Litterman model is also driven by their 0% weight in the equilibrium portfolio.

The impact of using an equilibrium portfolio in the Black-Litterman model is clearly visible. When compared to the stage switching model, the Black-Litterman model has a larger allocation to stocks and real estate, and a smaller weight to commodities during each stage. Stocks and real estate make up for 67% of the equilibrium portfolio on average, and the equilibrium portfolio does not allocate to commodities. The use of an equilibrium makes the Black-Litterman less flexible to incorporate the cyclical behaviour of asset class returns to improve performance. The Black-Litterman model is intended to do this, but we find it to decrease average excess returns.

On the other hand, the Black-Litterman model is more stable in its asset allocation over the business cycle than the stage switching strategy. The incorporation of an equilibrium causes the asset allocations per stage to deviate less from the full period allocation when compared to the stage switching portfolio. We find that the stage switching portfolio reinvests 71% of its portfolio on average when it switches between stages; for the Black-Litterman portfolio this is

55%. Furthermore, the Black-Litterman model accounts for the low n on which the estimates in the beginning of the sample are based. When the number of observations is low, the Black-Litterman model allocates only a small role to the views that are based on them.

Table 6.5

Out-of-sample portfolio performance comparison, mean-variance optimised, 1978 - 2015

This table compares both out-of-sample portfolios. All portfolios are optimised to maximise the mean-variance utility function for a level of risk aversion of 5. Asset weights for bonds and real estate are combined to allow for straightforward comparison, we follow the same approach for bonds and credits. The actual weights can be found in table A4 in this chapter's appendix.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: Out-of-sample stage switching model, Risk aversion level of 5					
Arithmetic annual excess return (%)	9.90	8.81 *	6.99 ***	17.57 ***	10.22
Annualized standard deviation (%)	11.97 ***	9.56	6.29 ***	8.89	9.64
Sharpe ratio	0.83	0.92	1.11	1.98	1.06
Average portfolio weights (%)					
Stocks & real estate	14.96	52.09	3.53	85.42	34.33
Bonds & credits	0.00	18.45	96.22	11.00	30.68
Commodities	44.37	28.31	0.25	3.58	21.93
Risk-free assets	40.66	1.15	0.00	0.00	13.06
Panel B: Out-of-sample Black-Litterman model, Risk aversion level of 5, n_o = 293					
Arithmetic annual excess return (%)	6.20 ***	7.39 ***	5.55 ***	20.30 ***	8.76
Annualized standard deviation (%)	9.10	9.33	9.08	10.32	9.46
Sharpe ratio	0.68	0.79	0.61	1.97	0.93
Average portfolio weights (%)					
Stocks & real estate	22.86	53.37	26.80	97.84	45.16
Bonds & credits	51.16	27.25	73.20	2.16	41.69
Commodities	25.98	19.37	0.00	0.01	13.15
Risk-free assets	0.00	0.00	0.00	0.00	0.00
Differences in allocation	38.73	9.52	23.27	12.42	15.31

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Table 6.6 shows the performance of both strategies over each business cycle for which the models are calculated. We find that the stage switching model shows larger differences in the average excess returns, volatilities and Sharpe ratios per cycle. While this is partially driven by the variations in asset returns and volatilities over business cycles (Tables 4.4 and 4.5), we find the Black-Litterman model to be more stable in its performance over time. We conclude that the Black-Litterman model is not only more stable within business cycles, but also over different business cycles.

Table 6.6

Out-of-sample portfolio performance per business cycle, 1978 - 2015

This table compares both out-of-sample portfolios in terms of performance and allocation for each business cycle in our sample. The first business cycle is not included since it is used as input period. The second business cycle is not included due to its low n of 28. All portfolios are optimised to maximise the mean-variance utility function. Asset weights for bonds and real estate are combined to allow for straightforward comparison, we follow the same approach for bonds and credits.

Business Cycle	3rd	4th	5th	6th	Full sample
Panel A: Out-of-sample stage switching model, Risk aversion level of 5					
Arithmetic annual excess return (%)	10.20	4.30 ***	17.24 ***	9.78	10.22
Annualized standard deviation (%)	7.53 ***	7.34 ***	11.80 ***	10.61	9.64
Sharpe ratio	1.36	0.59	1.46	0.92	1.06
Average portfolio weights (%)					
Stocks and real estate	31.48	39.96	34.97	39.43	36.31
Bonds and credits	22.91	32.44	27.25	45.96	30.73
Commodities	14.83	13.36	34.34	14.61	19.90
Risk-free assets	30.78	14.24	3.45	0.00	13.06
Panel B: Out-of-sample Black-Litterman model, Risk aversion level of 5, n_o = 293					
Arithmetic annual excess return (%)	9.00	7.09 ***	9.35	8.07	8.76
Annualized standard deviation (%)	9.62	7.32 **	8.92	11.03 **	9.46
Sharpe ratio	0.94	0.97	1.05	0.73	0.93
Average portfolio weights (%)					
Stocks and real estate	43.61	50.24	41.57	40.32	45.16
Bonds and credits	44.12	41.10	40.17	46.18	41.69
Commodities	12.27	8.66	18.26	13.50	13.15
Risk-free assets	0.00	0.00	0.00	0.00	0.00
# Observations	108	123	88	99	446
% of time in this economic stage	24	28	20	22	-

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Another advantage of the Black-Litterman model is that it can be used business cycle as an addition to an existing portfolio. In this study we used the market portfolio for the equilibrium, however, it also possible to use a benchmark or specific portfolio as the equilibrium input. The Black-Litterman model can be used to enhance performance by deviating from this benchmark over the business cycle. This makes the Black-Litterman model useable by investment professionals to enhance portfolio performance. It allows them to have a structural approach to enhance portfolio performance by incorporating the cyclical behaviour of asset class returns into their asset allocation process. The impact of the cyclical behaviour can easily be managed through the value for tau or by adding constraints on the asset weights.

The Black-Litterman model solves the major issues of the stage switching portfolio at a cost of performance; the Sharpe ratio decreases from 1.06 to 0.93. On the one hand, we find that the stage switching portfolio realises a higher return for a comparable level of volatility. On the other hand, we find that the Black-Litterman model is more stable in its asset allocation and performance within business cycles, and over multiple business cycles. The Black-Litterman model also accounts for the number of observations that are used to establish views, making it less sensitive to estimates early on. Furthermore, the Black-Litterman can easily be used by investment professionals in combination with an existing portfolio strategy. Since it is difficult, if not impossible, to quantify these differences in terms of riskiness or performance, we expect the choice for either model to be dependent on the user's preferences in practice.

6.3.2 All portfolios compared

A comparison for the two out-of-sample models that are introduced in chapter 6 and the in-sample models is provided in Table 6.7. All portfolios are optimised to maximise the mean-variance utility function for risk-aversion level of 5. Asset allocations per strategy are not included as comparisons have already been made, omitting them allows to compare all strategies on one page. The corresponding asset allocations, and the performances for different levels of risk aversion can be found in the chapters were each portfolio was discussed (note that time periods are different for the in-sample comparisons of chapter 5 compared to the out-of-sample comparisons of chapter 6).

While there are differences between both out-of-sample models over the business cycle in terms of their asset allocation and performances, we find both models to capture the cyclical behaviour of average asset returns (Panels A and B). The Sharpe ratios of both out-of-sample models are close to that of the (optimal) in-sample stage switching model of Panel C. Furthermore, both models outperform our two fixed portfolios of panels D and E over three out of four stages.

Table 6.7

Portfolio performance comparison, mean-variance optimised, A = 5, 1978 - 2015

This table compares three in-sample portfolios with both out-of-sample portfolios. All portfolios are optimised to maximise the mean-variance utility function for a level of risk aversion of 5. The in-sample portfolios differs in performance from the tables of chapter 5 due to differences in the time periods that are analysed. Their calculation and through it asset allocation remained equal.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: Out-of-sample stage switching model					
Arithmetic annual excess return (%)	9.90	8.81 *	6.99 ***	17.57 ***	10.22
Annualized standard deviation (%)	11.97 ***	9.56	6.29 ***	8.89	9.64
Sharpe ratio	0.83	0.92	1.11	1.98	1.06
Allocation to risk-free assets (%)	40.66	1.15	0.00	0.00	13.06
Panel B: Out-of-sample Black-Litterman model, n_o = 293					
Arithmetic annual excess return (%)	6.20 ***	7.39 ***	5.55 ***	20.30 ***	8.76
Annualized standard deviation (%)	9.10	9.33	9.08	10.32	9.46
Sharpe ratio	0.68	0.79	0.61	1.97	0.93
Allocation to risk-free assets (%)	0.00	0.00	0.00	0.00	0.00
Panel C: In-sample stage switching model					
Arithmetic annual excess return (%)	4.58 ***	5.16 ***	6.85 *	19.07 ***	7.89
Annualized volatility	9.57 ***	5.67 ***	6.52 **	9.49 ***	7.79
Sharpe ratio	0.48	0.91	1.05	2.01	1.01
Allocation to risk-free assets (%)	25.71	0.00	0.00	0.00	8.07
Panel D: Fixed weight portfolio					
Arithmetic annual excess return (%)	1.25 ***	4.67 *	4.81 *	5.60 ***	3.78
Annualized volatility	4.55 ***	5.28	7.22 ***	5.19	5.61
Sharpe ratio	0.28	0.88	0.67	1.08	0.67
Allocation to risk-free assets (%)	0.00	0.00	0.00	0.00	0.00
Panel E: Market portfolio					
Arithmetic annual excess return (%)	2.52 ***	2.01 ***	6.37 ***	6.53 ***	4.04
Annualized volatility	6.37 **	6.57 **	4.57 ***	4.35 ***	5.71
Sharpe ratio	0.40	0.31	1.39	1.50	0.71
Allocation to risk-free assets (%)	34.72	34.72	34.72	34.72	34.72

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Besides for the outperformance over fixed strategies per stage, the out-of-sample portfolios also allow for risk taking when its compensation is highest. We clearly find that both out-of-sample models have much higher average returns and Sharpe ratios than the fixed models over the full period. Both models are able to increase their average returns for against equal or lower levels of volatility since they can opt for risk taking during recovery and slowdown, when the compensation for it is highest. This means that these models can earn proportionally higher returns for lower levels of volatility when compared to fixed allocation strategies. The Sharpe ratios of Panels D and E do not change for different risk-aversion levels. These strategies decrease volatility by adding risk-free assets over the whole period, which does not change the Sharpe ratios.

We find Sharpe ratios over the full period to increase from 0.67 for the fixed weight portfolio, and 0.71 for the market portfolio to 1.06 for the stage switching portfolio, and 0.93 for the Black-Litterman model. We conclude that incorporating the cyclical behaviour of asset class returns into portfolio optimisation improves portfolio performance by 31% to 57% in terms of Sharpe ratio out-of-sample.

Chapter 7

Conclusion

The cyclical behaviour of asset classes can be used to add value to portfolio optimisation by dynamically changing a portfolio's asset allocation over the business cycle. We identify three sources of value when incorporating the business cycle into portfolio optimisation. First, we find that during each business cycle stage, different asset classes perform best in terms Sharpe ratios. This is mainly driven by excess returns, but also by volatilities. Second, we find that the compensation for risk differs per business cycle stage. Using a different allocation per stage allows to invest in risky assets when their performance is best, and to mitigate risk when the compensation for risk is least. Third, adapting asset allocations before the business cycle stages change, adds value to portfolio performance. We find that the OECD CLI can be used as a leading business cycle indicator ex-ante to capture these three value drivers.

We propose two models to improve portfolio performance through incorporating these value drivers out of sample. The first is a stage switching model, which has a different asset allocation per stage of the business cycle. The second is a Black-Litterman model that is extended to incorporate views based on the business cycle stages. These models successfully capture the cyclical behaviour of asset classes by changing their asset allocation over the business cycle. The Sharpe ratios of these models are 31% - 57% higher in an out-of-sample analysis when compared to portfolios that have a fixed allocation over the business cycle.

We find that the stage switching model outperforms the Black-Litterman model; it offers a higher return for a comparable level of volatility over the full period. The Black-Litterman model, on the other hand, is less sensitive to its estimates, and adjusts for the number of observations that are used to assess the cyclical behaviour of asset classes. This makes the Black-Litterman model more stable in its performance and asset allocation, both within business cycles, and over multiple business cycles. Furthermore, the Black-Litterman can easily be used by investment professionals on top of an existing portfolio strategy to enhance its performance. The choice for either model depends on an investor's preferences in the end.

Limitations

In this chapter we discuss some of the limitations to our approach, whereas in the next chapter section we discuss the practical implications, we conclude by discussing recommendations for future research.

The biggest limitation to this study is that we use historic data to develop views and that we pool those data over the complete time period. We base our analysis on the pooled data over different business cycles, while in reality, no business cycle is equal to another. Business cycles differ not only in length, but also in terms of macroeconomic characteristics (for example, interest rates, inflation, GDP growth rates, employment rates and expectation of future business conditions). We do not adjust for these business cycle characteristics by pooling business cycle stages. With only six business cycles in our sample it is difficult to draw statistically significant conclusions on the influence of business cycle characteristics on asset performance, especially out of sample. Furthermore, we find that returns of assets are strongly influenced by events such as the dot.com bubble and the more recent real estate bubble for which we do not adjust by pooling data. Lastly, our models treat the most recent business cycle in the same manner as the first in our sample. Structural changes to the economy or to our asset classes are not included in our models.

In our analysis, the OECD CLI is used as a predictor for the business cycle. The lead time of the OECD CLI on the business cycle is variable over time. Using the OECD CLI does not guarantee to ability to lead business cycle stages in the future in a similar manner as was possible in the past.

The strategies we propose in our research require regular trading. Stage predictions change about three to four times per year, resulting in rebalances of 50-70% of portfolio value each time. This could have a large impact on the profitability of the out-of-sample strategies. It is very difficult to assess the impact of trading costs historically; this also depends heavily on the type of investor and the investor’s access to resources. We do not expect trading cost to have a large impact today or in the future; the asset classes we use are investable through index products. After the boom in the passive investment industry of the last decade, even retail investors are able invest in these products against very low trading costs (and management fees).

Practical implications

Both strategies we propose can be used by investors to improve portfolio performance by adjusting for the business cycle in their asset allocations. The strategies are easy to replicate, the required data that is easy to gather, and it is easy to invest in the asset classes through index products that are both liquid and have low management fees. Since the strategies we propose focus on asset allocation, investors are still able to select securities or express views within asset classes.

The stage switching model can be used to improve a portfolio's Sharpe ratio by 54% on average, compared to the fixed strategies in this study for $A = 5$. The model can be extended to satisfy the investor's preferences by adding constraints, such as a minimum or maximum weight to certain asset classes, or the maximum volatility per business cycle stage. Blitz and Van Vliet (2009) found that constraints in a business cycle based mean-variance approach can reduce extreme allocations, large rebalances, and can stabilise portfolio risk. However, an investor should keep in mind that constraints often decrease performance.

The Black-Litterman model can be used to improve a portfolio's Sharpe ratio by 34% on average, compared to the fixed strategies in this study for $A = 5$. The Black-Litterman can easily be tweaked for different parameters matching an investor's preferences. The reliance on the equilibrium can be adjusted through the value for n_0, and the level of risk aversion. It is also possible to put a restriction on the maximum value for tau to limit the maximum impact that views have on asset allocation. Furthermore, it is easy to add restriction to Black-Litterman model in a comparable way as for the stage switching model.

Another advantage of the Black-Litterman model is that it can be used as a tool to improve the performance of an existing portfolio. The model can do so by setting the equilibrium input to that of a specific allocation or benchmark instead of the market. The Black-Litterman model is then used to deviate from that allocation over the business cycle. This allows investors to have a structural approach to enhance portfolio performance by incorporating the cyclical behaviour of asset class returns into their investment process.

Recommendations for future research

We attempt to have a neutral view with regard to the type of investor that is central in this thesis. The strategies we propose are usable by both retail investors and the investment industry as a result. Our study can be extended to fit a particular group of investors and include the factors which influence their investment decisions in the real world. Examples for professional investors are: the legal environment, benchmarks, taxes, bonus structures, (pension) liabilities, limits on rebalancing, and liquidity requirements. Examples for retail investors are: consumption, (mortgage) liabilities, taxes, planned expenditures, life cycle investing and changes in risk appetite.

The Black-Litterman model we propose can be extended further to increase its performance, or to improve its practical use. The current Black-Litterman model does not allow for allocations to risk-free assets, which are found to add value for the stage switching portfolio. Neither does the model allow for short-selling. If the model would be extended for these possibilities, that could potentially further increase performance.

Both models can be extended to incorporate trading costs. Trading costs hurt performance, but incorporating them into the models could reduce this negative impact. For example, when trading is costly, the models could potentially make the asset allocations more similar between business cycle stages to reduce the amount of trading required when stages change.

Another addition to this study could be to expand the scope from the U.S. market to other markets, or even to multiple markets simultaneously. Foremost, this would investigate if our approach is also usable in different markets. In the case of multiple markets, this could allow the strategy to benefit from a recovery (characterised by high Sharpe ratios) in one market, when the U.S. is in expansion (characterised by low Sharpe ratios) to improve performance.

As a last addition, we expect to find potential improvements by adding sub-asset classes. Incorporating them could add value if they are found to exhibit different cyclical behaviour over the business cycle compared to the asset classes they are part of. Sub-asset classes could be assessed on a stand-alone basis; by including sub-asset classes and replacing the asset class as a whole. Blitz and Van Vliet (2009) find this to add value for equities in their approach to business cycle based portfolio optimisation. The potential of sub-asset classes could also be assessed within asset classes over the business cycle. For example, by allocating more to growth stocks during one stage, and more to value stocks during another, without changing the total allocation to stocks that is determined optimal for those stages.

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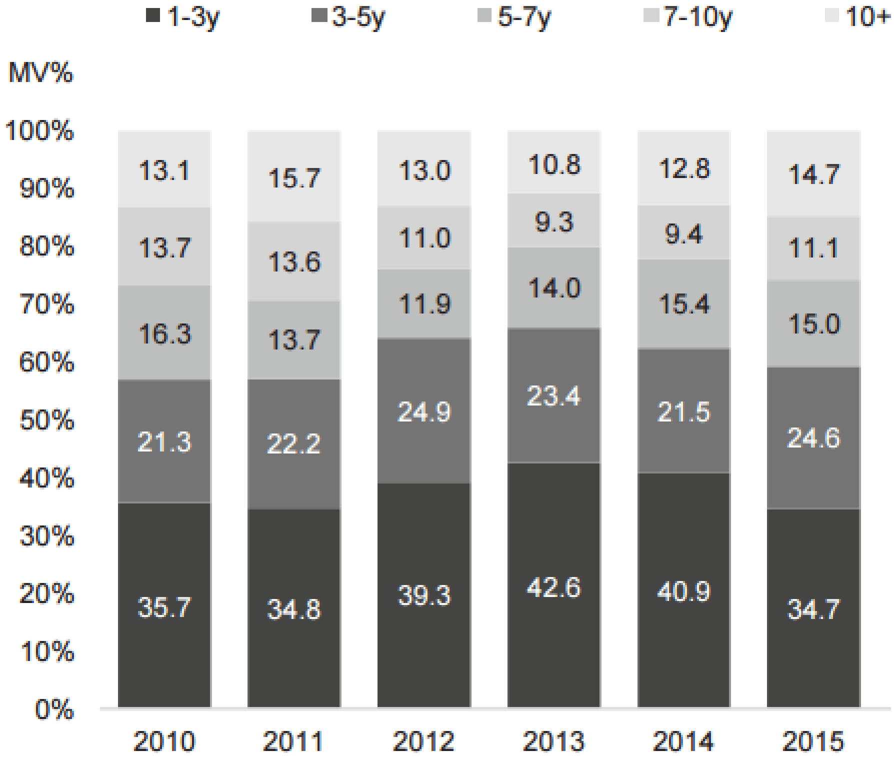
Appendix – Chapter 3

Figure A1
Historical composition US Treasury Bond Index, 2010 - 2015



Adapted from "Factsheet US Treasury" by Barclays (2016)

Figure A2
Asset class performance, logarithmic scale, 1973 =1, 1973 - 2015

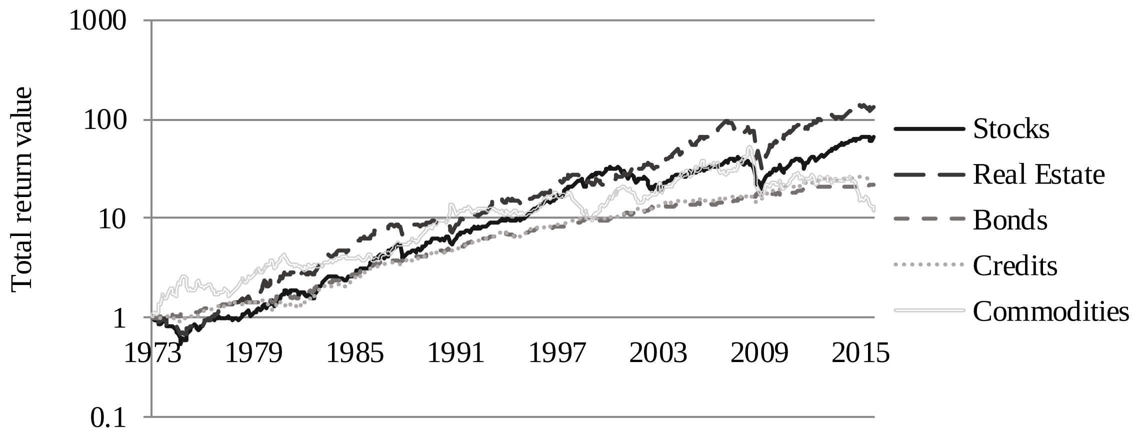


Figure A3

Historic market portfolio capitalisation, in billion USD, 1973 - 2015

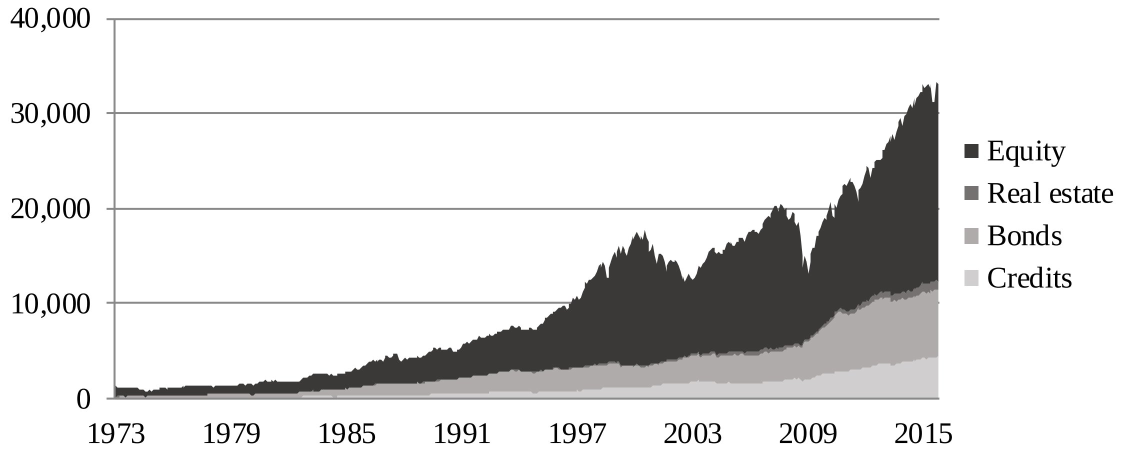
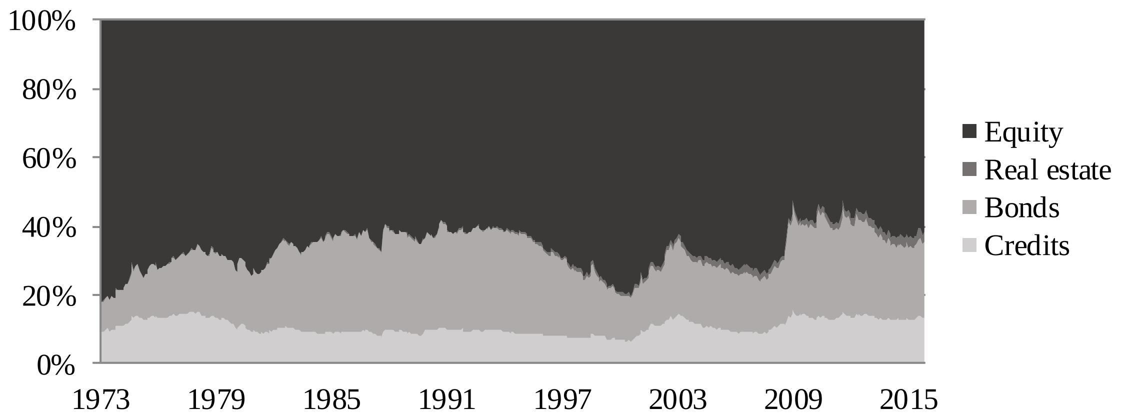


Figure A4

Historic market portfolio asset weights, 1973 - 2015



Appendix – Chapter 4

Table A1

Returns and volatilities based on total return data, 1973 - 2015

	Expansion	Downturn	Slowdown	Recovery	Full period
Stocks					
Arithmetic annual excess return (%)	7.68 *	1.49 ***	13.72 **	17.78 ***	10.15
Annualized volatility (%)	15.27	16.77	19.87 ***	13.07 ***	16.36
Sharpe ratio	0.50	0.09	0.69	1.36	0.62
Real estate					
Arithmetic annual excess return (%)	6.54 ***	7.73 **	13.85	20.67 ***	12.04
Annualized volatility (%)	13.57 ***	15.77 *	23.88 ***	15.20 **	17.41
Sharpe ratio	0.48	0.49	0.58	1.36	0.69
Bonds					
Arithmetic annual excess return (%)	4.96 ***	8.36 *	11.43 ***	5.36 ***	7.35
Annualized volatility (%)	4.43 ***	5.96 **	5.79 *	4.60 **	5.22
Sharpe ratio	1.12	1.40	1.97	1.17	1.41
Credits					
Arithmetic annual excess return (%)	4.91 ***	3.92 ***	15.16 ***	7.89	7.82
Annualized volatility (%)	5.25 ***	8.82 ***	8.02 **	5.83 ***	7.10
Sharpe ratio	0.94	0.45	1.89	1.35	1.10
Commodities					
Arithmetic annual excess return (%)	6.67	10.34 **	-2.36 ***	8.47	5.71
Annualized volatility (%)	19.42	24.12 **	23.92 **	16.78 ***	21.09
Sharpe ratio	0.34	0.43	-0.10	0.50	0.27
Airthmetic annual risk free rate (%)	5.29	6.58	4.39	3.41	4.88
% Of time in this economic stage	28	23	24	26	-
# Of observations	144	117	123	132	516

***, **, * Significantly different from the full period statistic at respectively the 1% , 5% or 10% level

Appendix – Chapter 5

Figure A5

Efficient frontier, full period, 1973 - 2015

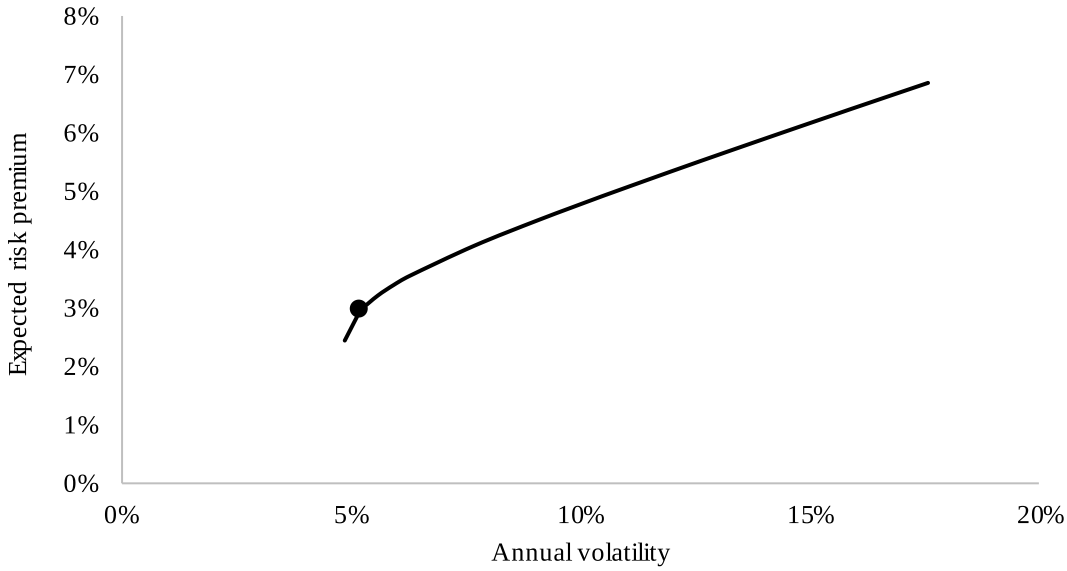


Figure A6

Optimal asset allocation on the efficient frontier, full period, 1973 - 2015

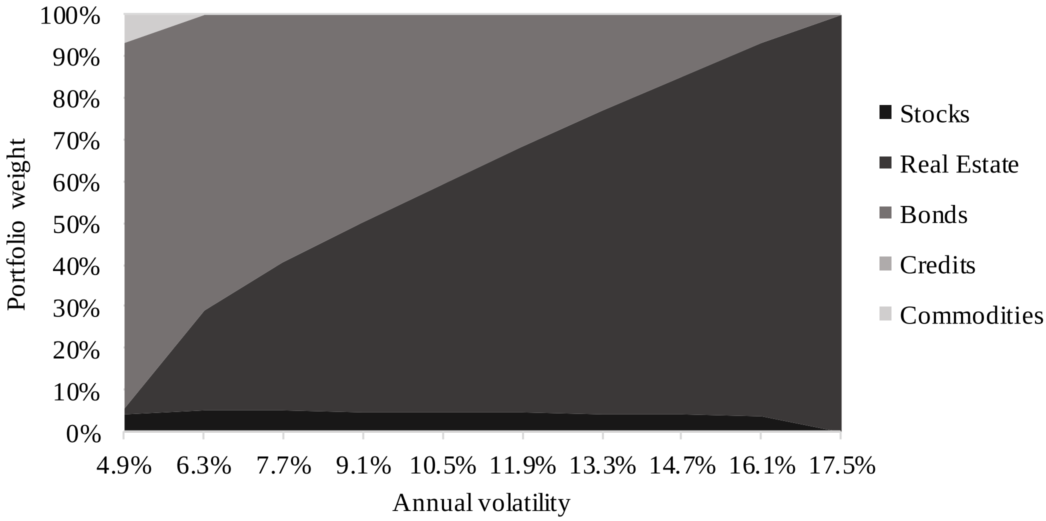


Figure A7

Efficient frontier, during expansion, 1973 - 2015

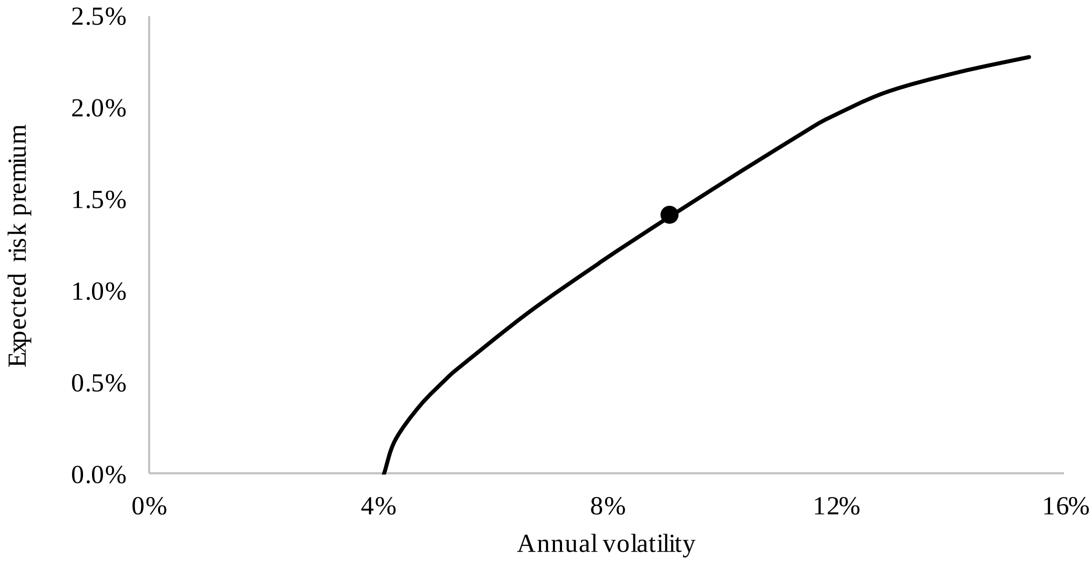


Figure A8

Optimal asset allocation on the efficient frontier, expansion, 1973 - 2015

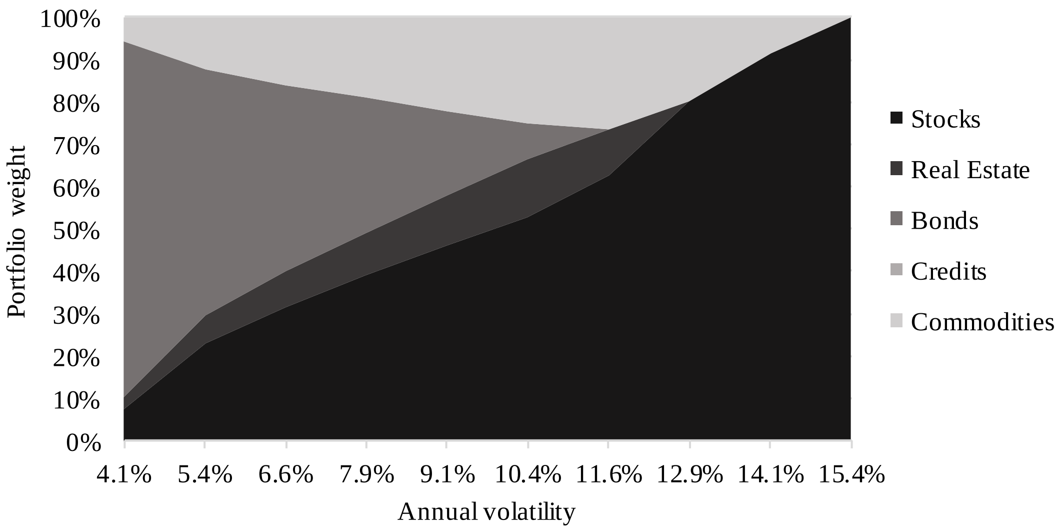


Figure A9
Efficient frontier, during downturn, 1973 - 2015

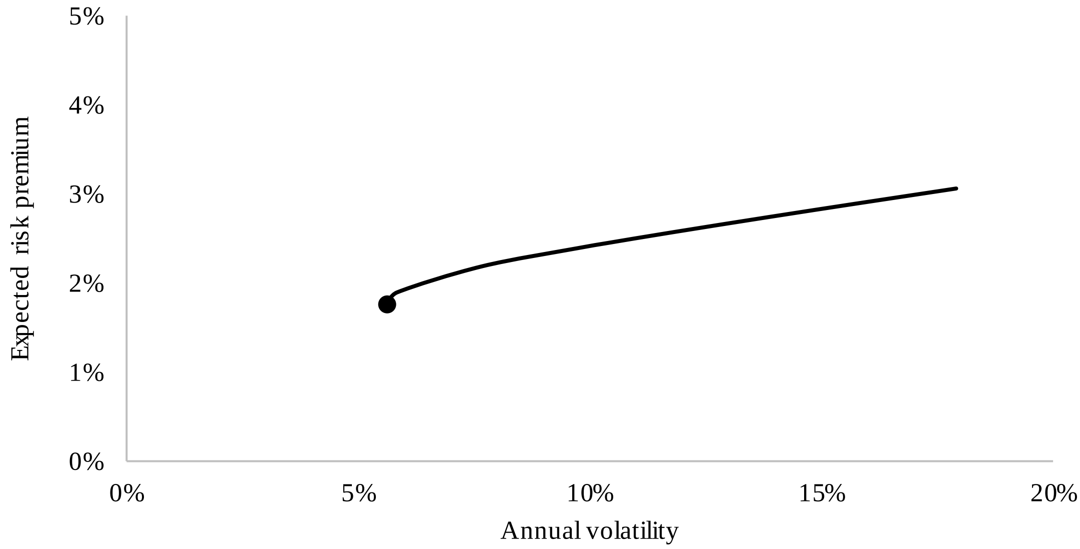


Figure A10
Optimal asset allocation on the efficient frontier, downturn, 1973 - 2015

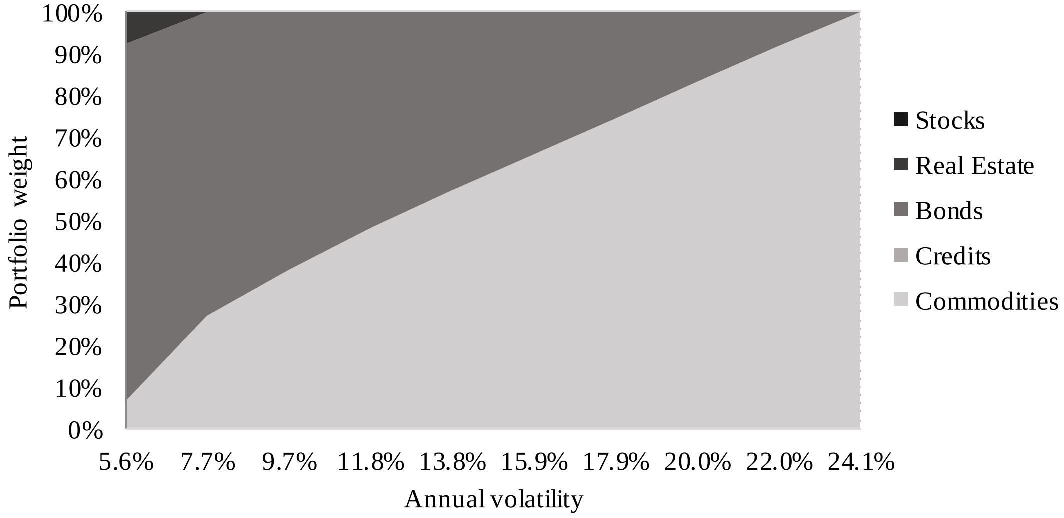


Figure A11
Efficient frontier, during slowdown, 1973 - 2015

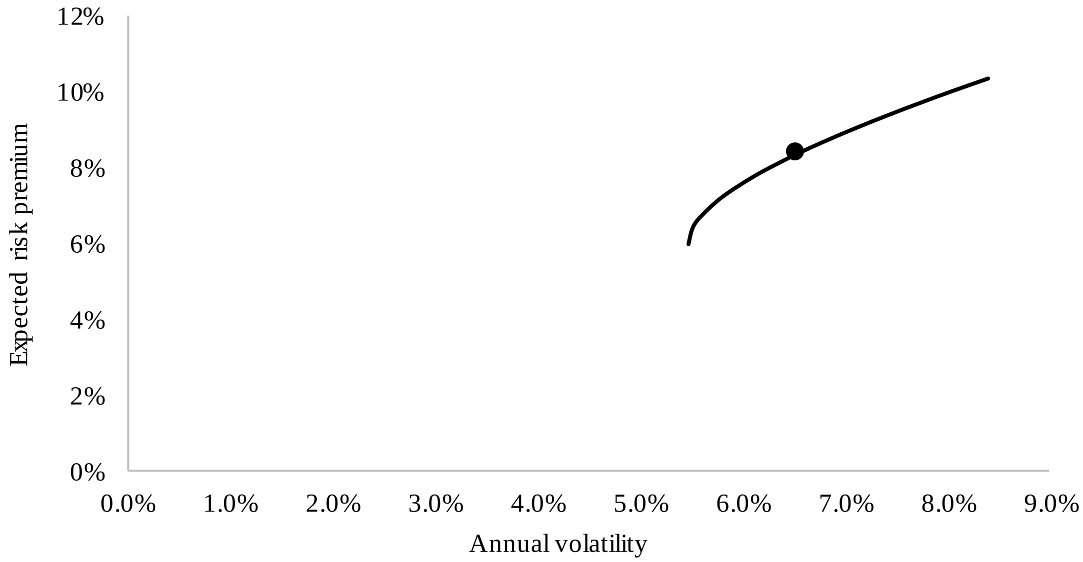


Figure A12
Optimal asset allocation on the efficient frontier, slowdown, 1973 - 2015

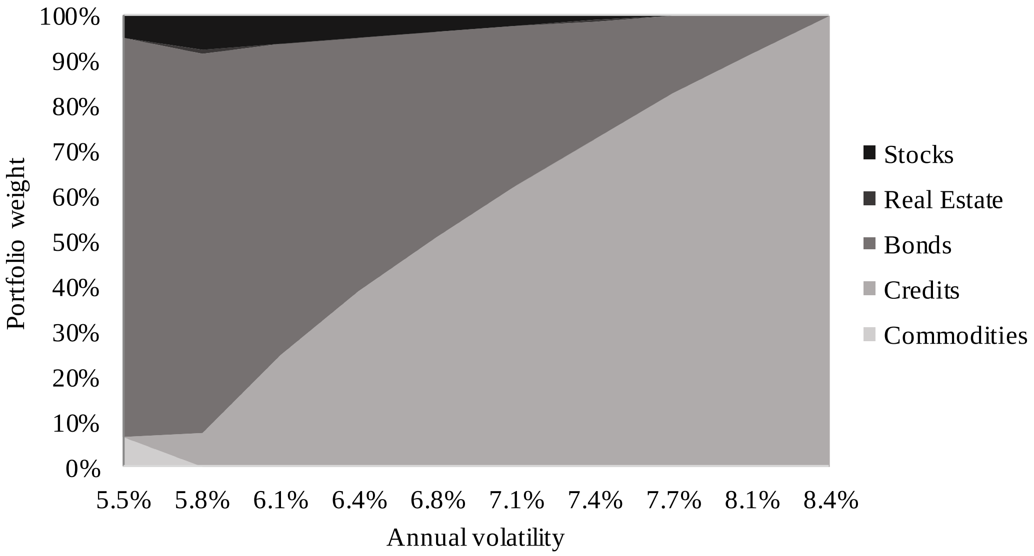


Figure A13

Efficient frontier, during recovery, 1973 - 2015

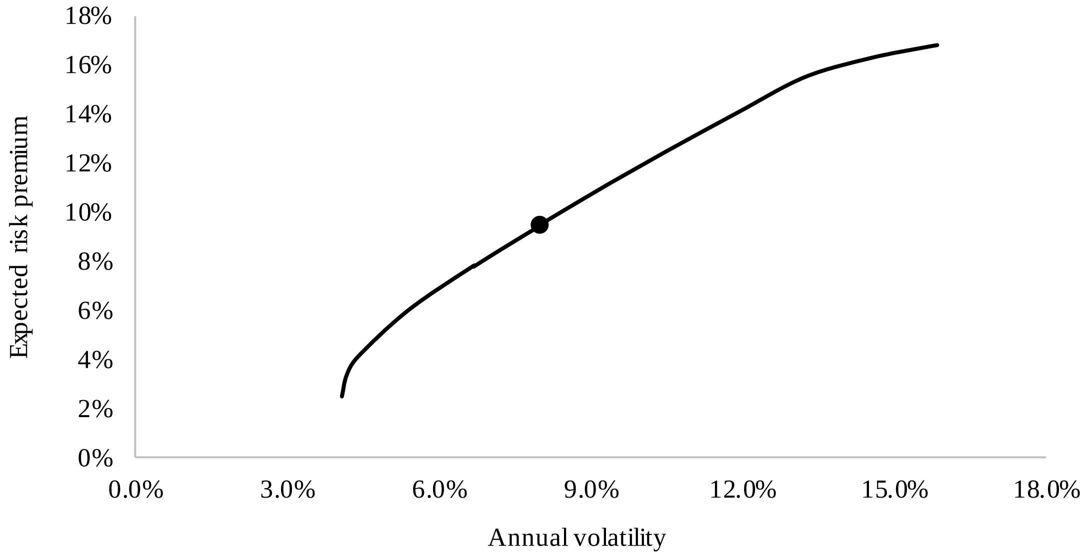


Figure A14

Optimal asset allocation on the efficient frontier, recovery, 1973 - 2015

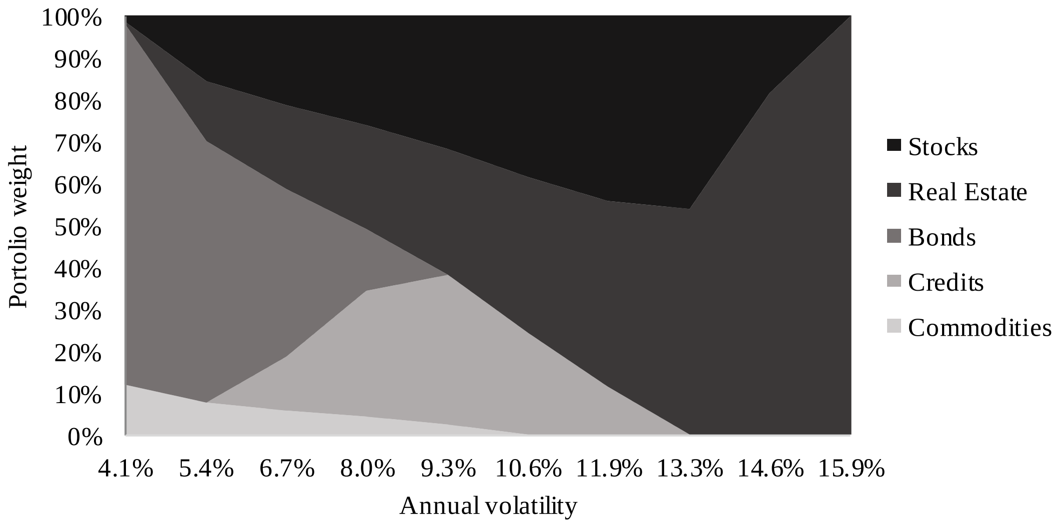


Table A2

Business cycle measurement and prediction, Sharpe ratio optimised, 1973 - 2015

Table 5.4 with the combined allocation to stocks and real estate and the combined allocation to bonds and credits.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: fixed weight portfolio					
Arithmetic annual excess return (%)	0.16 ***	3.79	4.88 ***	5.71 ***	3.20
Annualized volatility	4.58 ***	5.18	7.11 ***	5.03	5.51
Sharpe ratio	0.03	0.73	0.69	1.14	0.58
Portfolio weights (%)					
Stocks and real estate	21.46	21.46	21.46	21.46	21.46
Bonds and credits	77.99	77.99	77.99	77.99	77.99
Commodities	0.55	0.55	0.55	0.55	0.55
Panel B: Stage switching portfolio, OECD CLI based					
Arithmetic annual excess return (%)	4.39 ***	4.57 ***	6.70	15.90 ***	7.01
Annualized volatility	13.58 ***	5.92 ***	6.34 ***	8.28 *	9.56
Sharpe ratio	0.32	0.77	1.06	1.92	0.73
Portfolio weights (%)					
Stocks and real estate	43.74	29.57	0.00	71.43	34.17
Bonds and credits	0.00	65.73	100.00	19.31	45.30
Commodities	56.26	4.70	0.00	9.25	20.53
Panel C: Stage switching portfolio, OECD GDP based					
Arithmetic annual excess return (%)	1.95 ***	1.88 ***	8.38 ***	11.14 ***	5.75
Annualized volatility	11.88 ***	5.82 ***	6.10 ***	8.89	8.77
Sharpe ratio	0.16	0.32	1.37	1.25	0.65
Portfolio weights (%)					
Stocks and real estate	73.77	2.70	4.55	62.92	38.38
Bonds and credits	0.00	85.18	95.45	34.72	50.95
Commodities	26.23	12.12	0.00	2.36	10.67
Difference in portfolio weights of panel B and panel C (%)	30.03	26.87	4.55	15.41	9.86

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Appendix – Chapter 6

Figure A16

Expected excess returns during expansion in our rolling window analysis

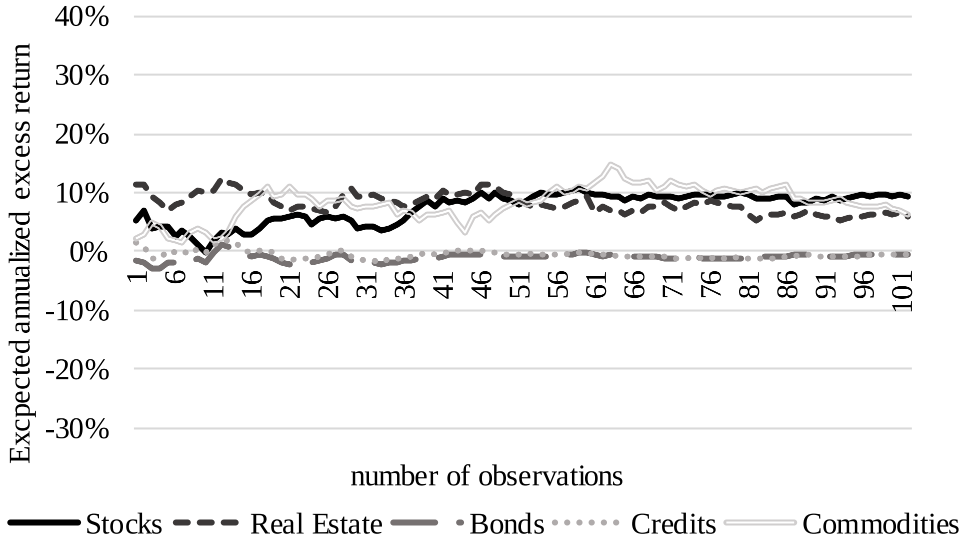


Figure A17

Expected excess returns during downturn in our rolling window analysis

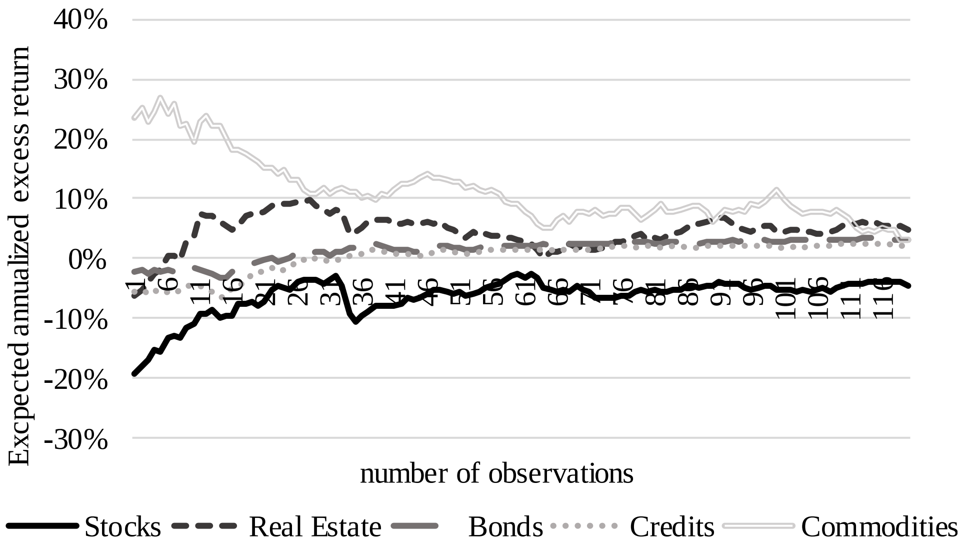


Figure A18

Expected excess returns during slowdown in our rolling window analysis

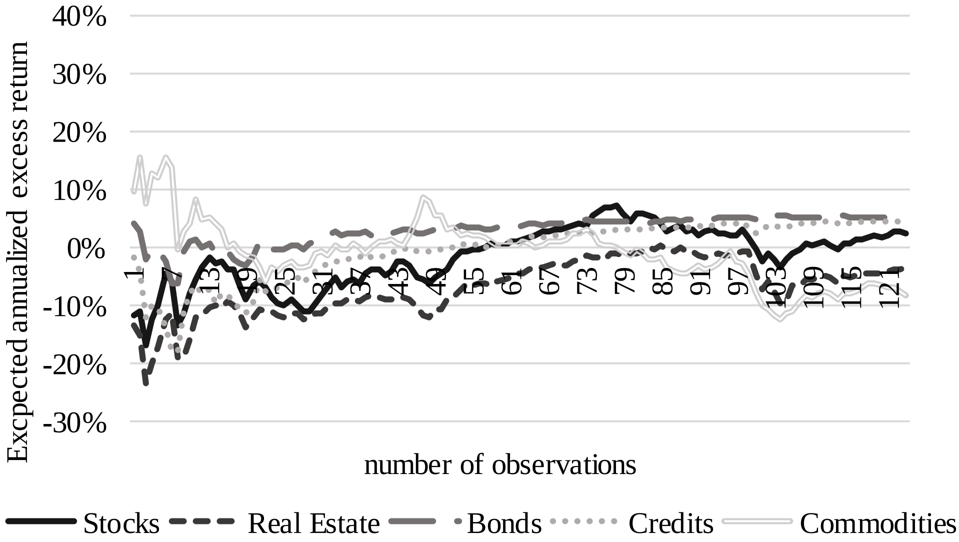


Figure A19

Expected excess returns during recovery in our rolling window analysis

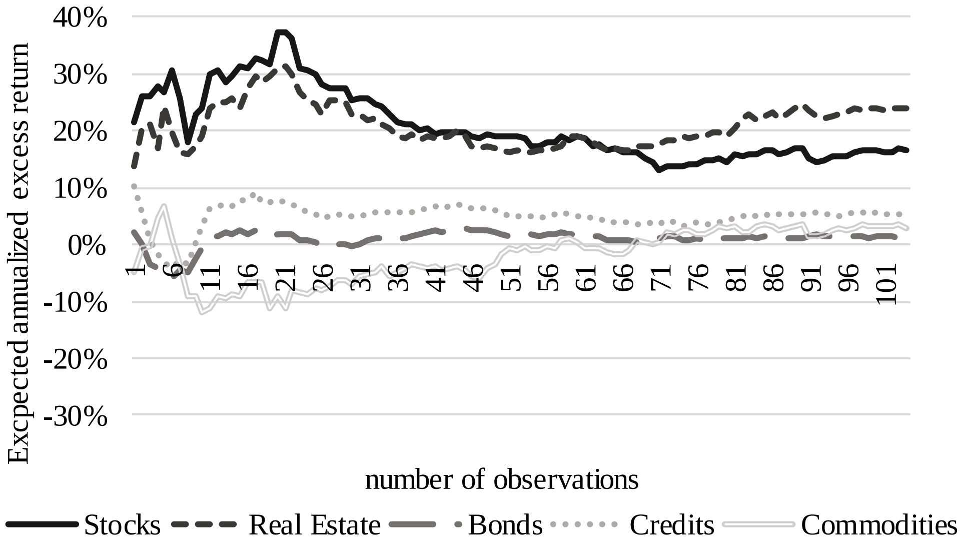


Figure A20

Historic correlations of asset classes with stocks, 1978 - 2015

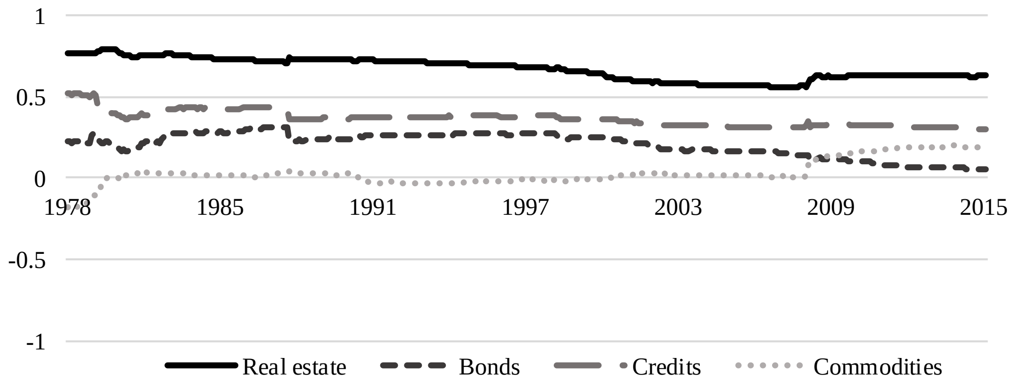


Figure A21

Historic correlations of asset classes with real estate, 1978 - 2015

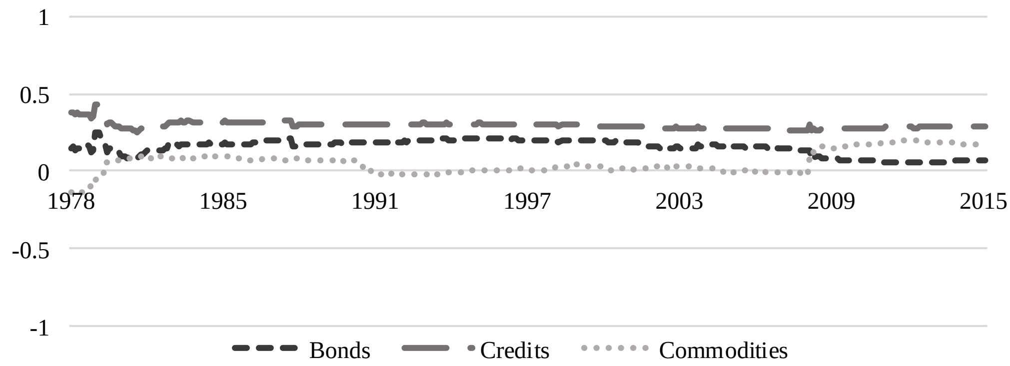


Figure A22

Historic correlations of bonds, credits and real estate, 1978 - 2015

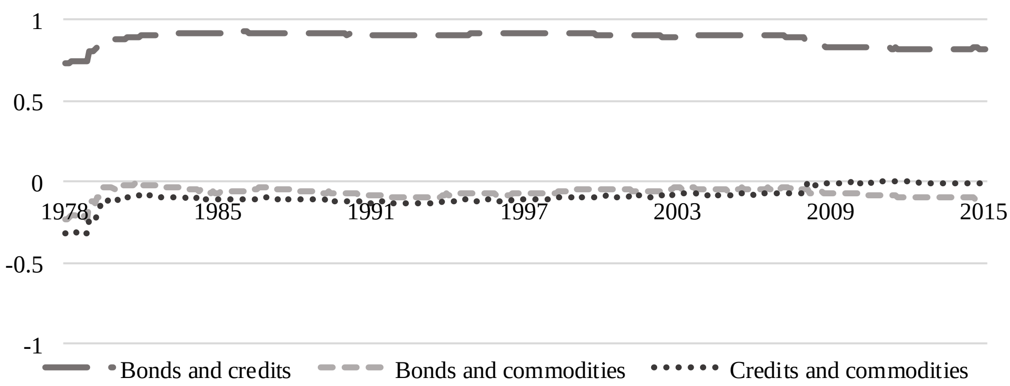


Table A3

Black-Litterman out-of-sample portfolio performance, n_o = 293, 1978 - 2015

	Expansion	Downturn	Slowdown	Recovery	Full period
			Risk aversion level of 1		
Arithmetic annual excess return (%)	11.46	8.51 ***	6.97 ***	24.86 ***	11.83
Annualized standard deviation (%)	15.44 ***	11.80	9.11 ***	11.48	12.51
Sharpe ratio	0.74	0.72	0.77	2.17	0.95
Average portfolio weights (%)					
Stocks	15.46	8.69	16.31	49.70	20.07
Real estate	2.00	37.67	0.08	50.30	19.38
Bonds	21.84	3.59	0.73	0.00	7.96
Credits	0.00	7.68	82.87	0.00	22.60
Commodities	60.71	42.38	0.00	0.00	29.98
			Risk aversion level of 5		
Arithmetic annual excess return (%)	6.20 ***	7.39 ***	5.55 ***	20.30 ***	8.76
Annualized standard deviation (%)	9.10	9.33	9.08	10.32	9.46
Sharpe ratio	0.68	0.79	0.61	1.97	0.93
Average portfolio weights (%)					
Stocks	19.99	37.82	26.79	67.68	34.83
Real estate	2.88	15.56	0.01	30.16	10.33
Bonds	51.16	27.06	6.21	0.00	24.58
Credits	0.00	0.19	66.99	2.16	17.11
Commodities	25.98	19.37	0.00	0.01	13.15
			Risk aversion level of 9		
Arithmetic annual excess return (%)	3.91 ***	6.53 **	5.21 ***	17.72 ***	7.29
Annualized standard deviation (%)	6.57 ***	8.00	8.72	9.28 **	8.10
Sharpe ratio	0.60	0.82	0.60	1.91	0.90
Average portfolio weights (%)					
Stocks	25.24	37.91	31.12	62.14	36.59
Real estate	0.95	5.94	0.00	19.16	5.27
Bonds	58.23	44.09	14.56	1.13	33.47
Credits	0.00	0.00	54.32	17.32	16.63
Commodities	15.57	12.06	0.00	0.25	8.04

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.

Table A4

Out-of-sample portfolio performance comparison, mean-variance optimized, 1978 - 2015

This table compares both out-of-sample portfolios. All portfolios are optimized to maximize the mean-variance utility function for a level of risk aversion of 5.

	Expansion	Downturn	Slowdown	Recovery	Full period
Panel A: Out-of-sample stage switching model, Risk aversion level of 5					
Arithmetic annual excess return (%)	9.90	8.81 *	6.99 ***	17.57 ***	10.22
Annualized standard deviation (%)	11.97 ***	9.56	6.29 ***	8.89	9.64
Sharpe ratio	0.83	0.92	1.11	1.98	1.06
Average portfolio weights (%)					
Stocks	8.83	4.03	3.04	43.09	12.30
Real Estate	6.14	48.06	0.49	42.33	22.03
Bonds	0.00	18.45	95.93	5.93	29.69
Credits	0.00	0.00	0.29	5.07	0.98
Commodities	44.37	28.31	0.25	3.58	21.93
Risk-free assets	40.66	1.15	0.00	0.00	13.06
Panel B: Out-of-sample Black-Litterman model, Risk aversion level of 5, n_o = 293					
Arithmetic annual excess return (%)	6.20 ***	7.39 ***	5.55 ***	20.30 ***	8.76
Annualized standard deviation (%)	9.10	9.33	9.08	10.32	9.46
Sharpe ratio	0.68	0.79	0.61	1.97	0.93
Average portfolio weights (%)					
Stocks	19.99	37.82	26.79	67.68	34.83
Real estate	2.88	15.56	0.01	30.16	10.33
Bonds	51.16	27.06	6.21	0.00	24.58
Credits	0.00	0.19	66.99	2.16	17.11
Commodities	25.98	19.37	0.00	0.01	13.15
Risk-free assets	0.00	0.00	0.00	0.00	0.00

***, **, * Significantly different from the full period statistic at the 1%, 5% and 10% level, respectively.