Original Article

Dynamic strategic asset allocation: Risk and return across the business cycle

Received (in revised form): 11th March 2010

Pim van Vliet
(PhD, Vice President) is a Senior Portfolio Manager with the Quantitative Equities team of Robeco. His primary focus is Robeco's low-volatility strategies, including conservative equities. He joined Robeco in 2005 as a Senior Quantitative Researcher in the Quantitative Strategies department with responsibility for the allocation research. He has published among others in the *Journal of Banking and Finance*, *Management Science* and the *Journal of Portfolio Management*. He is a regular speaker at international conferences and is a guest lecturer at several universities. Van Vliet holds a PhD and an MSc (cum laude) in Financial and Business Economics from Erasmus University, Rotterdam.

David Blitz
(PhD, Vice President) is the co-head of Quantitative Strategies with Robeco. He is responsible for all equity-related quantitative research. The key tools that have been developed in this area are proprietary stock selection models and portfolio optimization algorithms. He started his career in 1995 at Robeco, and has published papers in a.o. the *Journal of Portfolio Management*. Blitz holds a PhD in Business Economics and an MSc in Econometrics (cum laude) from Erasmus University, Rotterdam, and is registered with the Dutch Securities Institute.

Correspondence: Pim van Vliet, Coolsingel 120, NL 3011 AG, Rotterdam, The Netherlands
E-mail: p.van.vliet@robeco.nl

ABSTRACT We propose a practical investment framework for dynamic asset allocation across different phases in the business cycle, which we illustrate using a sample of US data from 1948 to 2007. We identify four phases in the business cycle and find that these capture pronounced time variation in the risk and return properties of asset classes. Time variation is also observed in the risk of a traditional, static strategic asset mix. In order to stabilize risk across the business cycle, we propose a dynamic strategic asset allocation approach, which has the potential to enhance expected return as well. The proposed investment framework is found to be robust to variations in the variable composition of the business cycle indicator and can easily be extended with different economic variables and/or additional assets.

Journal of Asset Management (2011) **12,** 360–375. doi:10.1057/jam.2011.12; published online 28 April 2011

Keywords: asset allocation; economic regimes; business cycle; portfolio choice; time-varying risk; time-varying return

INTRODUCTION

The asset allocation decision is known to be very important, and determines about 80–90 per cent of return variance (see, for example, Brinson *et al* (1991); Ibbotson and Kaplan (2000); and Statman (2001) for a discussion of these findings). Thus, investors carefully determine an appropriate long-term strategic asset allocation (SAA) policy, for example, by engaging in an asset liability management study. In practice, strategic asset allocation often turns into *static* asset allocation, with a fixed allocation to different asset classes. Although it is known that the risk and return properties of asset classes may vary over the business cycle[1], it is common practice to assume constant risk/return parameters for SAA purposes[2], resulting in one portfolio with constant weights. However, although the resulting SAA portfolio is static in terms of composition, its risk and return characteristics may actually exhibit significant time variation over the cycle.

A popular way to exploit time variation in returns is to apply a tactical asset allocation (TAA) overlay on the portfolio, as described by, for example, Dahlquist and Harvey (2001). However, as the objective of a TAA program is usually to maximize returns within a certain stand-alone risk budget, for example, a tracking error or value-at-risk limit, it does not offer a solution to time-varying overall portfolio risk. A TAA strategy may in fact turn out to exacerbate the tendency of the SAA portfolio to become more risky during 'bad' economic times, which is particularly undesirable for a risk-averse investor. As Cochrane (1999) points out, a risk-averse investor may prefer a portfolio with a lower Sharpe ratio in a world with time-varying risk and return, in case it offers protection during times of financial distress. Another approach is to use a regime-switching framework, as in Ang and Bekaert (2002, 2004).[3] This approach is based on statistical properties of the underlying assets and is typically used to identify two regimes.[4] Ang and Bekaert (2004) argue that the economic mechanism behind their regimes is likely the world business cycle. The main drawback of the regime-switching approach is its complexity, as a result of which investment professionals may be reluctant to rely on these models for real-life decision making.[5]

In this article, we propose a simple and transparent framework for dynamic strategic asset allocation (DSAA) based on the business cycle. In contrast to a traditional TAA strategy, this DSAA framework aims at enhancing portfolio return while at the same time stabilizing portfolio risk across the business cycle. Moreover, in contrast to more complex regime-switching models, which derive regimes from the return characteristics of the assets themselves, our approach uses economic data to model the business cycle directly. By focusing on economic fundamentals, the DSAA framework is designed to be closer to investment practice. The primary objective is not statistical optimality, but to bridge the gap between research analyst and investor by concentrating on intuitive economic relations and transparency. Instead of providing estimated probabilities of being in a particular regime at any point in time, we can explicitly determine the prevailing phase of the business cycle, which enables us to define and compare several dynamic asset allocation strategies. We illustrate the DSAA framework with a sample of US market data over the 60-year period from 1948 to 2007. Specifically, we combine four economic indicators (the credit spread, earnings yield, ISM and the unemployment rate) to identify four phases of the business cycle (expansion, slowdown, recession and recovery).[6] As our business cycle phases do not depend on statistical properties of asset classes, we can easily consider a broad opportunity set instead of focusing on a limited set of assets. In addition to equities, bonds and cash, we include small caps, value versus growth, credits and commodities in our analysis. Our framework is intended to help long-term investors design a transparent and practically feasible dynamic strategic asset allocation strategy over the business cycle.

Empirically, we find that the risk of a static SAA portfolio tends to increase during bad times, which is undesirable for a risk-averse investor. In addition to risk, the average return of many assets is also found to be highly dependent on the prevailing economic phase. For example, most assets exhibit above-average returns during recessions and recoveries and below-average returns during expansions and slowdowns. We show that investors can improve the performance of their strategic asset allocation by taking into account the risk and return properties of each asset class conditional on the phase in the business cycle. We first examine a classic tactical asset allocation approach, which concentrates on maximizing portfolio return during each economic phase. However, we find that this approach is suboptimal from a risk perspective, as it tends to increase risk systematically, and during bad times in particular. In order to address this concern, we propose a dynamic strategic asset allocation approach, which is successful at stabilizing portfolio risk across the business cycle, while at the same time offering the potential to enhance portfolio return. The key difference is that DSAA explicitly accounts for the interaction between tactical and strategic positions, which TAA ignores. We show that our empirical results are robust to changing the variables in the business cycle model, with considerable potential for further improvement. Finally, we argue that outsourcing a DSAA strategy to an external manager is more challenging than outsourcing a traditional TAA strategy. Investors could try to enforce their TAA managers to behave in a DSAA-consistent manner by imposing business cycle-dependent constraints, for example, by setting time-varying asset class bandwidths. Alternatively, investors could decide to fully integrate DSAA into their own strategic asset allocation policy.

The article proceeds as follows. The next section discusses the data and methodology, after which we present the empirical results. The final section concludes.

METHODOLOGY

Modeling the business cycle

The NBER is well known for determining official recessionary periods. NBER data are of little use for real-life dynamic asset allocation purposes though, as the NBER only classifies a period as either expansion or recession after the fact. Owing to this hindsight, the NBER data are only suitable for *ex post* explanatory analyses and not for *ex ante* decision making. This is also recognized by Gorton and Rouwenhorst (2006), who use the NBER business cycle classification for gaining insight into the risk and return properties of commodities over the cycle.[7]

In order to address this concern, we propose an alternative, forward-looking business cycle indicator. Our indicator uses only information that is actually available *ex ante* and offers the additional advantage of resulting in a more balanced distribution of observations across economic phases. In the appendix, we describe in detail how we combine four well-known economic indicators into one overall business cycle indicator, which can take on four different states. The four phases are schematically illustrated in Figure 1. In the 'expansion' phase, the combination of four economic indicators is both positive and rising. In the 'slowdown' phase, the level is still positive, but conditions are worsening. In the 'recession' phase, both level and direction are negative, whereas in the 'recovery' phase the level is still negative, but improving. We will refer to the expansion and slowdown phase as 'good times' and recession and recovery as 'bad times'.

We also show that our business cycle indicator matches fairly well with the 'official' NBER business cycle classification, although we fully acknowledge that our method may be improved upon with a more

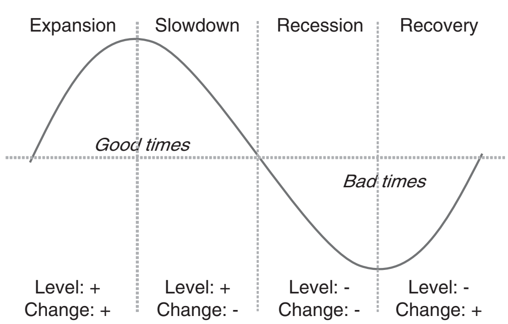

Figure 1: Business cycle with four phases.

sophisticated approach. However, the indicator suffices for the purposes of this article, namely to compare various dynamic strategic asset allocation approaches based on a business cycle framework, and to estimate the potential for risk/return improvement that is offered by these approaches. Furthermore, we will show that our main results are robust to variations in the variable composition of the business cycle model.

Asset allocation strategies

We consider the following eight asset classes and investment styles: US large-cap equities, US small-cap equities, US value equities, US growth equities, US credits, US Treasuries, commodities and cash.[8,9] All returns are in US dollars. The sample period is from January 1948 to December 2007, spanning a total of 60 years. We use a monthly data frequency.

As a base-case strategic asset allocation policy, we consider a static strategic asset allocation portfolio, denoted by SAA, which invests every month 25 per cent in large-cap equities, 25 per cent in Treasuries and 25 per cent in cash (core assets) and 5 per cent in value equities, 5 per cent in growth equities, 5 per cent in small-cap equities, 5 per cent in credits and 5 per cent in commodities (satellite assets). Next, we consider several dynamic asset allocation approaches that are based on our business cycle indicator. Each alternative is based on optimizing the asset allocation for each of the four phases separately, where for each alternative we use a different set of restrictions. In order to make a fair assessment of the added value of the optimized dynamic strategies, we compare them not only to our base-case static SAA portfolio but also to a second SAA strategy, which is optimized full sample for maximum return without taking into account the business cycle, that is, assuming that asset returns are IID. We denote this strategy by SAA-O and impose the restriction that it has the same absolute risk as our base-case SAA portfolio and the same constraints on asset weights as our dynamic, business cycle-based strategies. In the spirit of Merton (1971), our SAA-O approach represents the solution to a myopic (one period) problem, whereas our dynamic asset allocation strategies, which explicitly assume that asset returns are not IID, represent intertemporal hedging demands based on the business cycle.[10] An overview is given in Table 1.

Our first alternative that explicitly takes the business cycle into account is a tactical asset allocation strategy, in which we optimize the portfolio in each phase of the cycle for maximum expected return, subject to a 1 per cent tracking error limit. By using a tracking error constraint, we ensure that the optimized portfolios do not exhibit extreme deviations from the static SAA reference

Table 1: Definition asset allocation strategies

	SAA-O	*TAA*	*TAA-C*	*DSAA*
Panel A: Optimization approach				
Full-sample versus phase-based	full-sample	phase-based	phase-based	phase-based
Panel B: Asset weight restrictions				
Core assets (%)	0–100	0–100	0–100	0–100
Satellite assets	0–10	0–10	0–10	0–10
Panel C: Relative risk constraints				
Tracking error limit (%)	—	1	1	1
Panel D: Absolute risk constraints				
Volatility limit full sample	$\sigma_{SAA\ full\ sample}$	—	$\sigma_{SAA\ full\ sample}$	$\sigma_{SAA\ full\ sample}$
Volatility limit for each phase	—	—	—	$\sigma_{SAA\ full\ sample}$

portfolio, and we implicitly control transaction costs by forcing the optimizer to focus on the most attractive bets. The asset weights are required to be non-negative, to add to 1 and not exceed 10 per cent for the five satellite assets.[11] Weights for the three core assets are not constrained to a maximum value.

As it turns out that the base-case TAA approach structurally increases portfolio risk, we also consider an alternative tactical asset allocation approach (TAA-C, denoting constrained TAA), which is identical to the TAA approach, except for the additional constraint that overall volatility does not exceed overall volatility of the static SAA portfolio. By definition, this approach prevents a structural increase in portfolio risk. However, it does not offer a solution for the tendency of the static SAA portfolio to become more risky during bad times. In fact, the TAA-C approach turns out to exacerbate this effect. In order to stabilize portfolio risk across the business cycle, we therefore consider a final alternative, which we call a dynamic strategic asset allocation strategy. With this approach, we impose the additional restriction that not only overall portfolio volatility, but also volatility during each of the four phases does not exceed the overall volatility level of the static SAA.

All portfolio optimizations are full sample because of data limitations. An approach based on in-sample strategy development, followed by an out-of-sample test, is practically infeasible.[12] With the full-sample approach, we have an average of 15 years of data for each of the four economic phases, which is already a relatively short period of time for strategic asset allocation purposes. In other words, with an in-sample/out-of-sample approach, the in-sample phase would already require most (or all) of our sample, leaving hardly any (or no) remaining data for an out-of-sample test. Furthermore, as mentioned before, the primary objective of this article is to present a framework for dynamic asset allocation, and the empirical data are only meant to illustrate the potential of such an approach. Our results do not aim to represent real-life investment strategies.

RESULTS

Risk and return across the cycle

We begin our empirical analysis by investigating the risk and return of the assets in our sample across the different economic phases. Table 2 shows the correlations between several asset classes during each phase of the business cycle. These estimates are based on monthly data, but we note that quarterly data yield similar outcomes. The average correlations of equity with bonds, credits and commodities are 0.13, 0.29 and 0.00, respectively, over the total 60-year sample period. Interestingly, however, we find that equity-bond correlations are negative during slowdowns and become positive during recessions and recoveries. This means that diversification benefits fade when they are needed most. By contrast, we find that during recoveries the correlation

Table 2: Key correlations across different economic phases

	Equity–Bonds	*Equity–Credits*	*Equity–Commodities*
Panel A			
Full sample	0.13	0.29	0.00
Panel B			
Expansion	0.04	0.09	0.02
Slowdown	−0.16	0.12	0.02
Recession	0.15	0.35	0.02
Recovery	0.38	0.45	−0.12

Sample period 1948–2007.

between equities and commodities becomes negative, indicating more opportunities for diversification.

Table 3 shows the annualized volatility of each asset class, as well as the static SAA portfolio, across the different phases. We find that risk tends to be highest during recessions and recoveries (bad times). The full-sample volatility of the static SAA portfolio is 6.2 per cent, but this number varies between 5.6 per cent in good times and 6.6 per cent in bad times. This time-varying risk profile is mainly caused by (1) the increased risk of government and corporate bonds in bad times and (2) the increased equity–bond correlation during bad times discussed before. During recessions, the volatility of commodities decreases somewhat, and during recoveries the correlation of commodities with other asset classes becomes more negative. Equities show limited time variation in risk across the four phases in the business cycle.

Table 4 shows the excess (log-) returns of each asset class across the four phases. The SAA portfolio yields an average return of 2.9 per cent in excess of cash, but this return varies between 0.5 per cent during slowdowns and 4.8 per cent during recessions. This result is driven by the fact that equity returns are highest during recessions and lowest during slowdowns. This suggests that financial markets run ahead of the business cycle by about one phase. In other words, when the real economy slows down, equity markets already show disappointing returns because of the anticipated recession, whereas equity markets are already recovering when the real economy is still in recession. This implies that financial markets do not concentrate on current economic conditions, but also take into account expected future economic conditions. An important observation is therefore that bad times for the economy are not necessarily bad times for investors! During bad economic times, not only are risks higher, but returns also tend to be higher.

Interestingly, both the value premium (value versus growth) and the size premium (small versus large) are negative during

Table 3: Risk of asset classes for each economic phase

	Equity (%)	*Value (%)*	*Growth (%)*	*Small (%)*	*Credits (%)*	*Bonds (%)*	*Comm (%)*	*SAA (%)*
Panel A								
Full sample	14.2	14.0	15.4	18.9	6.4	4.7	15.6	6.2
Panel B								
Expansion	13.8	14.0	14.6	18.7	4.5	3.5	14.0	5.6
Slowdown	13.7	13.8	15.2	19.8	5.1	3.9	18.1	5.7
Recession	14.6	14.0	16.0	18.7	8.2	5.6	15.9	6.6
Recovery	13.9	13.3	15.3	18.5	6.4	5.1	15.7	6.4

Risk is defined as annualized volatility. Sample period 1948–2007.

Table 4: Annualized excess return of asset classes during each economic phase

	Equity (%)	*Value (%)*	*Growth (%)*	*Small (%)*	*Credits (%)*	*Bonds (%)*	*Comm (%)*	*SAA (%)*
Panel A								
Full sample	5.6	6.4	4.7	6.6	0.5	0.6	1.3	2.9
Panel B								
Expansion	3.7	3.2	3.9	0.9	−1.0	−0.4	5.7	1.8
Slowdown	0.2	1.9	−1.6	2.9	−3.0	0.1	−0.2	0.5
Recession	10.2	11.1	9.0	12.7	1.6	1.4	−3.7	4.8
Recovery	5.1	7.1	3.3	9.4	3.0	1.2	6.1	3.4

Sample period 1948–2007.

expansions, while being positive during the other three phases of the cycle. Also noteworthy is the lack of a credit risk premium (credits versus Treasuries) in our sample. Credits outperform government bonds during recessions and recoveries, but underperform during expansions and slowdowns. Commodities deliver high returns during expansions and recoveries, while lagging during slowdowns and recessions. In summary, we observe various pronounced cyclical patterns in the return characteristics of the different asset classes, which motivate the examination of business cycle-based asset allocation strategies.

Business cycle-based asset allocation

In this section, we compare the static SAA approach with the business cycle-based asset allocation strategies defined in the methodology section. In Table 5, we show the optimized portfolio weights and in Table 6 we show the risk/return characteristics of the various approaches.

The SAA-O full-sample optimized portfolio exploits the value and small-cap premium to the maximum extent possible, and it makes maximum use of the attractive risk/return properties of commodities. Nevertheless, it only manages to improve the excess return by a statistically insignificant 0.20 per cent, while also failing at stabilizing the risk of the portfolio over the cycle.

The first dynamic allocation strategy that we consider is the base-case TAA approach, which, for each phase, selects a portfolio that is optimized for highest expected return, taking into account the restrictions outlined in the methodology section. The average excess return of the TAA approach is 3.71 per cent per annum, compared with 2.90 per cent for the static SAA approach. The difference is 0.81 per cent, which, given the tracking error budget of 1 per cent, translates into an information ratio of 0.81. This performance is not only economically significant, but also highly statistically significant, with an associated *t*-value of 6.29. The return differential ranges from 0.45 per cent during slowdown phases to 1.08 per cent during recessions. However, not only portfolio return, but also portfolio risk is increased. In fact, the TAA portfolio exhibits a systematically higher level of risk than the

Table 5: Optimized business cycle-based allocation strategies

	Equity (%)	*Value (%)*	*Growth (%)*	*Small (%)*	*Credits (%)*	*Bonds (%)*	*Comm (%)*	*Rf (%)*
Panel A: SAA								
Static base-case	25	5	5	5	5	25	5	25
Panel B: SAA-O								
Static optimized	19	10	—	10	—	25	10	26
Panel B: TAA								
Expansion	39	—	3	2	—	26	10	21
Slowdown	22	10	—	9	—	31	5	23
Recession	29	10	—	8	—	34	3	15
Recovery	24	10	—	10	10	23	9	14
Panel C: TAA-C								
Expansion	34	—	4	—	—	19	10	33
Slowdown	14	10	—	10	—	27	4	35
Recession	25	10	—	9	—	31	1	24
Recovery	19	10	—	10	10	20	10	21
Panel D: DSAA								
Expansion	39	—	5	—	—	21	10	25
Slowdown	19	10	—	10	—	31	5	25
Recession	20	10	—	9	—	27	—	34
Recovery	18	10	—	10	10	19	10	23

Sample period 1948–2007.

SAA reference portfolio. Compared with the static SAA portfolio, overall volatility increases from 6.17 per cent to 6.82 per cent, and volatility is also higher in each of the four separate economic phases. One of the reasons for this is that the TAA portfolios systematically overweight equities and underweight cash compared with the static SAA portfolio. In other words, the additional return generated by the TAA approach is, at least partly, simply a reward for additional beta exposures, instead of true alpha. In fact, the outperformance of the TAA portfolio vis-à-vis the SAA portfolio exhibits a correlation of 0.62 with the absolute return of the SAA portfolio. The importance of making the distinction between performances as a result of true alpha instead of implicit beta in the context of tactical asset allocation is also stressed by Lee (2000).

In order to address this concern, we consider the TAA-C approach, which is specifically aimed at preventing an increase in overall portfolio risk. Table 6 shows that overall portfolio risk of the TAA-C strategy is indeed equal to that of the static SAA strategy. Consistent with this, the structural overweight of equities observed for the TAA strategy is not present with the TAA-C strategy. The average excess return improvement drops to 0.61 per cent (equivalent to an information ratio of 0.61, with a *t*-value of 4.70), ranging from 0.43 per cent during expansions to 0.81 per cent during recoveries. During slowdowns, recessions and recoveries, the TAA-C strategy overweights value stocks and small-caps, and underweights growth stocks. During expansions, the strategy underweights value and small caps and is neutral on growth stocks. Credits are always underweighted, except during recoveries. Commodities are overweighted during expansions and recoveries, neutral during slowdowns and underweighted during recessions.

Although the TAA-C approach is successful at controlling overall portfolio risk, it does not succeed in achieving a stable risk. Both the static SAA strategy and the TAA-C strategy exhibit pronounced time-varying risk across economic phases. For the static SAA strategy, this is simply due to the time-varying risk characteristics of asset classes. The TAA-C strategy, however, goes one step further by actively reducing risk during low-return phases (expansions and slowdowns), in order to be able to take on more risk during the highest return phase (recessions). In other words, instead of countering the tendency of the SAA strategy to exhibit more risk during bad economic times, the TAA-C strategy turns out to exacerbate this behavior. As mentioned before, this is particularly undesirable for a risk-averse investor, see Cochrane (1999).

In order to address this concern, we propose an approach that we call dynamic

Table 6: Risk and return characteristics of business cycle-based allocation strategies

	Return					*Risk*				
	SAA (%)	*SAA-O (%)*	*TAA (%)*	*TAA-C (%)*	*DSAA (%)*	*SAA (%)*	*SAA-O (%)*	*TAA (%)*	*TAA-C (%)*	*DSAA (%)*
Panel A										
Full sample	2.90	3.10	3.71	3.51	3.38	6.17	6.17	6.82	6.17	6.17
Outperformance	—	0.20	0.81	0.61	0.48	—	—	—	—	—
(t-statistic)	—	*(1.54)*	*(6.29)*	*(4.70)*	*(3.71)*	—	—	—	—	—
Panel B										
Expansion	1.78	1.98	2.35	2.21	2.44	5.60	5.70	6.07	5.35	6.17
Slowdown	0.45	0.99	0.90	0.90	0.95	5.68	5.98	5.83	4.95	5.66
Recession	4.80	4.75	5.88	5.55	4.97	6.55	6.46	7.54	6.98	6.17
Recovery	3.37	3.76	4.42	4.18	4.12	6.36	6.16	7.06	6.32	6.17

Risk is defined as annualized volatility and return is excess return over cash. Outperformance is defined as the return difference with the SAA reference portfolio. Sample period 1948–2007.

strategic asset allocation, or DSAA. This approach is specifically designed to stabilize risk across the business cycle. Specifically, the portfolios are optimized subject to the constraint that not only overall volatility, but also volatility during each phase does not exceed 6.17 per cent. Looking at the resulting portfolios, we observe that the main change compared with the TAA-C approach is the weight of equities, which is now chosen in such a way that risk across different economic phases is stabilized. The average return enhancement is equal to 0.48 per cent, implying an information ratio of 0.48 (with a *t*-value of 3.71). The return improvement ranges between 0.50 per cent and 0.75 per cent during expansions, slowdowns and recoveries. During recessions, the main improvement is not an increase in expected return (which is enhanced by only 0.17 per cent in this phase), but a reduction of risk, as volatility can be seen to drop from 6.55 per cent to 6.17 per cent. Stable risk across the business cycle is desirable for a risk-averse investor with a constant risk budget. To summarize, the DSAA approach is able to stabilize risk across the business cycle, while, at the same time, improving expected return.

Robustness

The case for dynamic strategic asset allocation hinges on two premises, namely the ability to identify time-varying risk and time-varying return opportunities. In reality, the latter condition is likely to be most challenging. However, even if expected returns are considered to be unpredictable, there remains a case for DSAA, although a simplified variant that is solely aimed at stabilizing portfolio risk. In this section, we will examine the robustness of our finding that, at the very least, a business cycle-based approach is able to identify time-varying risk characteristics and can be used to adjust the portfolio composition accordingly.

We begin by examining the risk of the asset classes in our sample during official NBER expansions and contractions. The results are shown in Table 7. Consistent with the results for our business cycle model, we observe that the risk of each class is significantly higher during ‘bad times’ (NBER contractions) compared with ‘good times’ (NBER expansions). This provides corroborating evidence for the existence of time-varying risk that is linked to the business cycle.

The business cycle model that has been used throughout this article appears to be effective at identifying time-varying risk *ex ante*. We may wonder, however, how sensitive this result is to our choice of variables that, together, comprise the business cycle model. Therefore, we examined the effects of leaving out any one of the four variables in the business cycle model. The results of this analysis are shown in Table 8. We observe that removing any one of the four variables in the business cycle model does not degrade its ability to identify time-varying risk. If anything, this aspect of the model appears to improve somewhat, as the dispersion in volatility across economic phases tends to widen.

If DSAA is applied with the sole objective to stabilize portfolio risk, one might consider tailoring the business cycle model specifically toward this purpose. Empirically, volatility is often found to be persistent, that is, if volatility has recently been high (low), it is likely to remain high (low) in the following

Table 7: Risk of asset classes for each economic phase

	Equity (%)	*Value (%)*	*Growth (%)*	*Small (%)*	*Credits (%)*	*Bonds (%)*	*Comm (%)*	*SAA (%)*
NBER expansions	13.3	13.1	14.4	17.5	5.5	4.2	14.4	5.7
NBER contractions	18.1	17.6	19.6	24.8	9.8	6.3	20.7	8.2

Risk is defined as annualized volatility. Sample period 1948–2007.

Table 8: SAA portfolio risk across the business cycle for alternative business cycle models

	Regime model sensitivity analysis					
	Base case (%)	*Excl. credit spread (%)*	*Excl. earnings yield (%)*	*Excl. ISM (%)*	*Excl. unemployment (%)*	*Plus equity volatility (%)*
Expansion	5.60	5.54	5.14	5.25	5.48	5.31
Peak	5.68	5.80	5.84	6.09	5.65	5.39
Recession	6.55	6.53	6.67	6.52	6.58	6.83
Recovery	6.36	6.56	6.78	6.62	6.36	6.48

Risk is defined as annualized volatility. Sample period 1948–2007.

period. The literature, which takes a purely statistical approach toward identifying regimes in the time-series properties of asset class returns, also tends to find alternating periods with high and low volatility. Inspired by these results, we examined 12-month realized equity volatility as a potential additional (or alternative) factor for the business cycle model.[13] Consistent with what we would expect *a priori*, we find that 12-month realized equity volatility is above average and increasing during NBER contractions. The last column in Table 8 shows that when the variable is added to our base-case business cycle model, it becomes better at identifying time-varying risk characteristics. If 12-month realized equity volatility is added as a fifth factor, the spread between the maximum and minimum volatility across economic phases increases from less than 1 per cent to over 1.5 per cent.

We conclude that, if the primary objective of a business cycle approach is considered to be stabilizing portfolio risk over time, our base-case business cycle model does not paint an overly optimistic picture, as we find that even stronger results may be obtained by considering additional variables.

SUMMARY AND IMPLICATIONS

We propose a practical investment framework for dynamic asset allocation across the business cycle, which we illustrate with a sample of data for the US market over the period from 1948 to 2007. We construct a business cycle indicator on the basis of a combination of four well-known economic variables, which can take on four different states. The business cycle indicator is found to relate reasonably well to the official NBER business cycle. Our first empirical result is that the risk and return properties of asset classes are highly dependent on the prevailing economic phase. This finding motivates the examination of various dynamic asset allocation strategies. As a benchmark, we take a traditional SAA portfolio, which has static weights, but a time-varying risk/return profile over the business cycle. In particular, risk tends to go up in bad times, which is undesirable for a risk-averse investor. An alternative, full-sample optimized static SAA portfolio is neither able to stabilize risk across the cycle nor does it succeed in significantly enhancing return.

One way investors can exploit the business cycle is by developing a TAA strategy, which is designed for a maximum outperformance in each phase of the cycle. The drawback of this approach is that absolute portfolio risk is increased systematically, and in particular once again, in bad times. In order to stabilize absolute portfolio risk and simultaneously enhance portfolio returns, we propose a dynamic strategic asset allocation approach. We have shown that the proposed DSAA approach is robust to variations in the variable composition of the business cycle model and that the approach can easily be extended with different economic variables and/or additional assets. The DSAA framework is intended to bridge the gap between research analyst and investor by concentrating on intuitive economic relations and transparency, in contrast to existing statistically driven techniques, such as Markov regime-switching models. For investors who are skeptical toward exploiting time variation in asset returns, we have shown that DSAA can still serve as a robust tool for stabilizing portfolio risk across the cycle, with considerable potential for further improvement.

Interestingly, the aim for stable absolute performance across the business cycle through dynamic strategic asset allocation leads to markedly different portfolios and performance characteristics than the aim for stable outperformance through tactical asset allocation. Absolute return investors bring down risk during bad times, whereas relative return investors increase risk during bad times. These opposing outcomes imply that it is essential to clearly specify the investment objectives, consistent with the finding by Binsbergen *et al* (2008) that a decentralized investment approach can lead to suboptimal portfolios.

Institutional investors who would like to implement a business cycle-based allocation approach need to choose between internal versus external management. In case of outsourcing, the challenge is to align the investment objectives of the investor with those of the external manager. Outsourcing is fairly straightforward if the objective is simply to enhance return. As we have seen, however, a TAA approach that concentrates on maximizing returns can have undesired consequences for the overall risk profile of the portfolio. A DSAA strategy with overall and business cycle-dependent constraints on absolute portfolio risk addresses this concern, but outsourcing this to an external manager is likely to be more challenging in practice. Risk monitoring should become more sophisticated and an *ex post* performance evaluation of the external manager should not focus solely on the realized outperformance and tracking error of the manager, but also evaluate whether the manager has been successful at stabilizing overall portfolio risk. In order to avoid these practical complexities, investors could decide to fully integrate DSAA into their internal strategic investment policy. Alternatively, investors might enforce their TAA managers to behave in a DSAA-consistent manner by imposing business cycle-dependent constraints (for example, bandwidths) on the exposure to each asset class. For example, in case a high-risk economic phase is identified, a TAA manager might be restricted from overweighting high-risk assets such as equities.

ACKNOWLEDGEMENTS

We appreciate the suggestions made by Roy Hoevenaars, Angelien Kemna, Laurens Swinkels, Artino Janssen, Jan Sytze Mosselaar, Jaap van Dam, an anonymous referee, seminar participants at the June 2009 State Street European Quantitative Forum and participants of the Robeco SAA seminar in November 2009. Financial support by the Robeco Group is gratefully acknowledged. Any remaining errors are the authors' responsibility.

NOTES

1. For example, Sa-Aadu *et al* (2006) examine diversification benefits of alternative assets across regimes and find that commodities and real estate offer a hedge during periods with low per capita consumption growth (economic bad times). Gorton and Rouwenhorst (2006) find that the diversification benefits of commodities in a balanced portfolio vary across the different phases in the business cycle.
2. For example, for strategic asset allocation purposes Hoevenaars *et al* (2007) and Bekkers *et al* (2009) suggest using long-term historical data for estimating volatilities and correlations, while deriving expected returns from a combination of long-term historical data, economic theory and current market circumstances.
3. Ang and Bekaert (2004) design a strategy that tries to exploit time variation in returns using the switching framework of Hamilton (1989). They find that dynamic asset allocation across two regimes improves return for country allocation and for allocation across equities, bonds and cash.
4. The approach can be extended to model more regimes. For example, Guidolin and Timmermann (2007) statistically identify four regimes (crash, slow-growth, bull

and recovery) to capture the joint distribution of stock and bond returns, which they use to derive a regime-based strategic asset allocation strategy. They also provide a good overview of the existing literature on this subject.

5. An econometrician is needed to estimate the regime-switching probabilities either with maximum likelihood or Bayesian techniques. The model must be kept simple with a limited number of assets because in the setup of Ang and Bekaert (2004) with 2 regimes and 6 assets, 19 parameters need to be estimated and one should check whether the estimates are not ill-behaved.
6. A detailed description of the model can be found in the appendix. In the robustness section, we show that the results do not critically depend on the inclusion of any of these four factors.
7. Actually, Gorton and Rouwenhorst (2006) go even one step further by distinguishing between early and late expansions and early and late recessions, on the basis of the *ex post* identification of each expansion and recession midpoint. This introduces an additional element of hindsight. Another drawback of this approach is that the frequency of the four resulting phases is quite unbalanced. Specifically, for our 60-year sample, early and late recessions in particular each contain only 8 per cent of the data points, which is equivalent to fewer than 5 years of observations.
8. For large-cap equity returns, we use the S&P 500 index. For value and growth returns, we use the MSCI BARRA value and growth indices, which are available from February 1975 onward, and before this we use data from Kenneth French (BV and BG). For small caps, we use the Russell 2000 index, backfilled with small-cap return data from Kenneth French before January 1979. Credit returns are based on the Lehman US Aggregate Corporate index, backfilled with data from Ibbotson (LT Corporate) before January 1973. US Treasuries are based on the Lehman US Aggregate Treasury index, backfilled with Ibbotson data (IT Government) before January 1973. Commodities are defined as the GSCI index, backfilled with the CRB spot index before January 1970. Cash is defined as the return on US 30-day T-bills.
9. As US value equities and US growth equities together (approximately) comprise US large-cap equities, the latter asset class might be considered redundant. Nevertheless, we prefer to include each of these asset classes because it is convenient when, later on, we distinguish between core and satellite asset classes.
10. This argument is also given by Ang and Bekaert (2002) in the context of their regime-switching model.
11. Jagannathan and Ma (2003) show that restricting portfolio weights is effectively a form of covariance matrix shrinkage. Diris *et al* (2008) stress the importance of shrinkage when determining an asset allocation strategy.
12. Goyal and Welch (2008) point out that many conditional variables may work well in-sample, but fail out-of-sample after they have been documented.
13. A forward-looking implied volatility indicator such as VIX might be even more appealing, but the data for such variables are not available with a history of 60 years.
14. The ISM data and unemployment data are final figures and could differ from the preliminary figures published earlier.
15. research.stlouisfed.org/fred2
16. www.econ.yale.edu/~shiller/data.htm
17. www.nber.org/cycles.html
18. We would like to stress that other macro or market factors can also be used. These four factors are used to illustrate how economic data can be used to construct a dynamic SAA framework.
19. We use median instead of mean in order to reduce the impact of outliers on the resulting z-scores.
20. If the factors are normally distributed and uncorrelated, then the economic score is also standard normally distributed. However, in practice we observe that the factors are positively correlated, especially during stressful periods.
21. In order to limit the transition of one phase to another because of noise (signal flip-flopping), we include an absolute threshold of 0.10. For example, if the combined indicator is $+0.05$ then this is within the bandwidth of -0.10 and $+0.10$, which means that we do not change phase and keep the same phase as in the previous month. The same threshold applies for 1-year changes, which should also exceed an absolute value of 0.10.

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APPENDIX

Construction of business cycle indicator

The philosophy behind our business cycle indicator is to combine a limited number of economically relevant variables using a simple and transparent model structure, aiming for a reasonably good match with the official business cycle as classified by the NBER. We acknowledge that by using a more sophisticated approach it would probably be possible to develop a superior model, but this is not our main objective. The number of possible variables is limited because we impose the requirement that a data history of at least 60 years should be available. We consider two market variables that have already been linked to the business cycle in the literature on conditional asset pricing, namely the credit spread (Chen *et al*, 1986) and the earnings yield (Campbel and Shiller, 1987), and two macro-economic variables that are also clearly linked to the cycle, namely the ISM (which is designed to be a leading economic indicator) and the unemployment rate (which is a widely used lagging economic indicator).

Table A1: Level and 1-year change of economic indicators for full sample (720 months) and recession periods (114 months)

	Full sample		*NBER contractions*	
	Level	*SD*	*Level*	*1-year change*
Credit spread	96.1	42.5	120	+27.8
Earnings yield (%)	7.2	3.1	9.5	+1.3
ISM index	54.5	8.0	43.2	−10.8
Unemployment (%)	5.6	1.5	6.0	+1.2

The credit spread is defined as the difference between Baa and Aaa corporate bond spreads from Moody's and the earnings yield is the E/P ratio of the S&P500. A high credit spread or high earnings yield indicates 'contraction', whereas low spreads or yields indicate 'expansion'. The ISM is the seasonally adjusted US manufacturers' survey production index and the unemployment rate is the seasonally adjusted US unemployment rate from the Bureau of Labor Statistics.[14] An ISM value above 0.50 or low unemployment indicates 'expansion' and an ISM below 0.50 or high unemployment indicates 'contraction'. All data are obtained from Datastream and before 1970 are backfilled using the FRED database[15] and for P/E using Robert Shiller's database.[16]

Figure A1 shows the monthly data for each of our four business cycle indicators, defined in the data section, over the full sample of 60 years. We observe different cycle lengths for each of the four factors. For the credit spread level, we observe three main phases: the credit spread is between 50 and 125 during most of the 1950s and 1960s, rising to 75–300 during the 1970s and 1980s and falling back to 50–125 starting from the 1990s onward. The earnings yield can be described in four phases. It varies between 8 and 16 per cent from 1948 to 1958, falling to 4–8 per cent during 1959–1973, going up again to 8–15 per cent during the 1973–1985 period and then varying between 2 and 8 per

Table A2: Distribution of four economic phases and transition matrix

Total no.	*NBER*	*From/To*	*Transition Matrix*			
			Expansion (%)	*Slowdown (%)*	*Recession (%)*	*Recovery (%)*
230	1	Expansion	93	3	—	3
95	6	Slowdown	6	83	11	—
238	101	Recession	2	3	90	4
144	6	Recovery	4	—	8	88

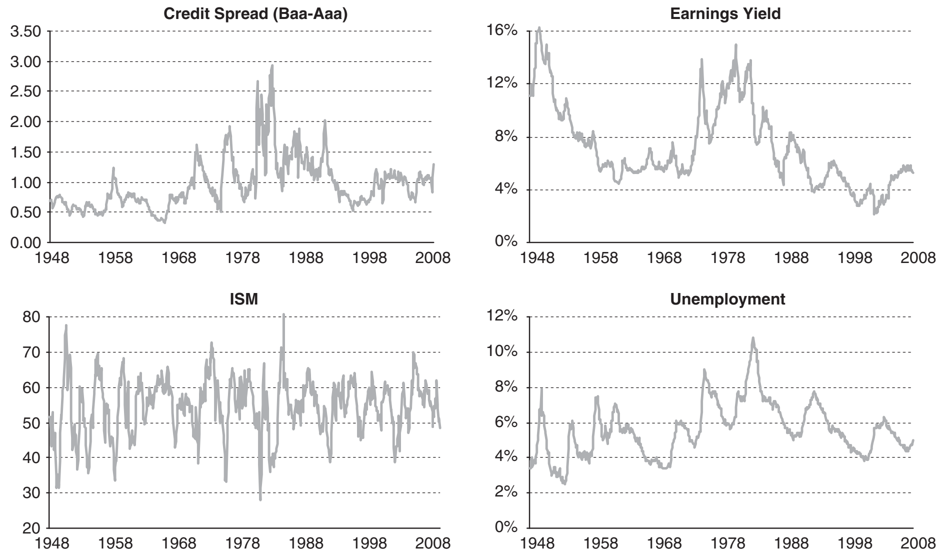

Figure A1: Time series of each conditioning variable. Monthly observations over the 60-year period from 1948 to 2007.

cent during the 1985–2007 period. The ISM factor fluctuates much more frequently, passing the neutral level of 0.50 either from either above or below about 30 times over this sample period. Finally, we observe that the unemployment rate passes the median value of 5.5 per cent about 15 times. Thus, the different cycles last between 2 and 20 years, depending on the variable under consideration.

We proceed by relating the economic indicators to the NBER business cycle indicator. NBER defines 114 out of the total 720 months in our sample as contraction period, or 16 per cent of all observations.[17] It is important to note that NBER classifies a contraction with hindsight, whereas our business cycle indicator only uses information available before the next month. Table A1 shows the average level and 1-year change of each indicator during the full sample and during NBER recession periods.

We observe that during NBER contraction periods (1) the credit spread is high and increasing, (2) earnings yield is high and increasing, (3) ISM is low and decreasing and (4) unemployment is high and increasing. Thus, we find that both the level and the 1-year change contain information about economic conditions. During NBER contraction periods, we observe that the four indicators, both in terms of level and change, deviate by about 0.5–1.0 standard deviations from their long-term average values.

In order to obtain a robust and broad indication of the condition of the US economy, we proceed by combining the four economic factors into one overall business cycle score.[18] We note that the main findings in this article are robust to leaving out any one of the four indicators. We standardize the four economic variables by deducting their full-sample medians[19] and by dividing by their full-sample standard deviations. To limit the impact of outliers and individual factors, we further cap the individual *z*-scores to a maximum of +3 and a minimum of −3. Finally, we combine the individual *z*-scores into one overall score by adding the individual scores and dividing by the square root of 4.[20]

On the basis of the combined indicator, we define four economic phases. In the ‘expansion’ phase, the combined indicator is both positive and increasing. In the ‘slowdown’ phase, the level is still positive, but conditions are worsening. In the ‘recession’ phase, both level and direction are negative, whereas in the ‘recovery’ phase the level is still negative, but improving. This classification is consistent with Gorton and Rouwenhorst (2006), who differentiate between early and late expansion and early and late recession using NBER slowdown and through data. However, the advantages of our approach are that (i) it is applicable in practice as the required data are readily available *ex ante* and (ii) the monthly observations are more evenly distributed across economic phases, leading to more statistical power.

Figure A2 shows the historical values of our economic indicator, together with the NBER contraction periods (shaded areas), for the full-sample period from 1948 to 2007. The economic indicator varies between +1.8 (1965) and −5.0 (1982). A positive score indicates ‘good times’, whereas a negative score indicates ‘bad times’. In general, we find that gradual increases in economic conditions are followed by abrupt downside shocks. The figure shows that a negative and/or falling indicator is associated with contraction periods. This finding is in line with the results of Table A1.

We translate the combined economic indicator into four phases, depending on its (i) level and (ii) 1-year change. For example, at the end of 2007 both the level and change were negative, which implies that the following period is classified as a recession phase.

Table A2 shows the distribution of the four economic phases and the accompanying transition matrix. The expansion and recession phases occur more often than slowdown and recovery phases. This can be explained by our earlier observation that gradual increases in economic conditions tend to be followed by rather abrupt declines in economic conditions. This asymmetry causes slowdowns in particular to be rather short lived. The transition matrix shows that the probability of staying in one phase from month to month is between 83 per cent and 93 per cent, whereas the probability of moving to another phase is 7–17 per cent. This translates into an average duration of each phase in the business cycle of about 9 months.[21]

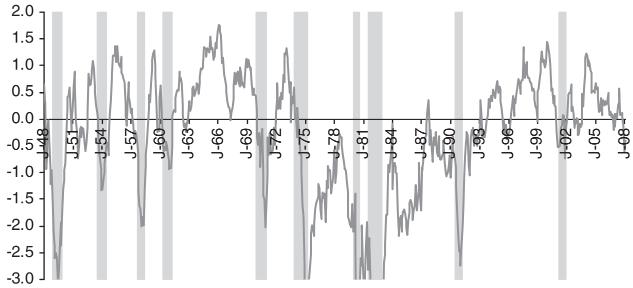

Figure A2: Time series of the combined economic indicator combined with NBER contraction periods. Monthly observations over the 60-year period from 1948 to 2007.

When our business cycle model indicates a state of recession, there is a 42 per cent chance that NBER will later on classify this month as a part of a contraction period. We find that 90 per cent of all NBER contraction periods falls within the model recession phase, whereas 10 per cent falls in either slowdown or recovery. Thus, NBER contraction periods coincide strongly with our economic indicator being negative and falling. All major contraction mid-points are predicted correctly, although the exact slowdown (start) and trough (end) are sometimes classified differently. Interestingly, the recession of the early 1990s is also correctly predicted. Stock and Watson (1992) argue that most leading indicators have difficulty predicting this particular contraction period.

To summarize, we have proposed a framework that can be used to translate economic variables into a business cycle indicator, which can take on four different states. With the four variables proposed in this article, the business cycle indicator is found to match reasonably well with the official business cycle, as reported by the NBER.