Dynamic Strategic Asset Allocation: Risk and Return across Economic Regimes

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ABSTRACT

We propose a practical investment framework for dynamic asset allocation across different economic regimes, which we illustrate using a sample of U.S. data from 1948 to 2007. We identify four regimes in the economic cycle and find that these regimes 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 allocation portfolio. In order to stabilize risk across the economic cycle we propose a dynamic strategic asset allocation approach, which has the potential to enhance expected return as well. The proposed approach is found to be robust to variations in the variable composition of the regime model and can easily be extended with different economic variables and/or additional assets.

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I. Introduction

The asset allocation decision is known to be very important, determining about 80-90% of return variance, see for example Brinson, Singer and Beebower (1991) and Ibbotson and Kaplan (2000). Realizing this, investors carefully determine an appropriate long-term strategic asset allocation (SAA) policy, e.g. by engaging in an asset liability management (ALM) 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 exhibit time-variation across economic regimes[1], it is common practice to assume constant risk/return parameters for SAA purposes[2], resulting in one portfolio with constant weights. Not surprisingly, this causes the static strategic portfolio to exhibit time-varying risk and return characteristics as well.

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, e.g. 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.

In this paper we describe a regime-based asset allocation approach which, contrary to a traditional TAA strategy, aims at enhancing portfolio return whilst, at the same time, stabilizing portfolio risk across the economic cycle. Our approach is based on linking the time-varying risk and return characteristics of the investment opportunity

[1] For example, Sa-Aadu, Shilling and Tiwari (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 economic cycle.

[2] For example, for strategic asset allocation purposes Hoevenaars, Molenaar and Schotman (2007) and Bekkers, Doeswijk and Lam (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.

set over the economic cycle to the asset allocation decision. We propose a simple and transparent framework for dynamic strategic asset allocation based on economic regimes, which we illustrate with a sample of data for the U.S. market over the sixty year period from 1948 until 2007. While many other papers use statistical properties of the assets themselves for regime definitions[3], we propose a more fundamental approach which uses economic data for defining different regimes. An essential feature of our approach is flexibility with regard to the specific set of variables and the model structure that are used. The key difference with the statistical approach is that, instead of providing estimated probabilities of being in a particular regime at any point in time, our approach explicitly identifies the prevailing regime, which enables us to derive transparent regime-based asset allocation strategies. Specifically, we consider a regime model which uses four economic indicators (the credit spread, earnings yield, ISM and the unemployment rate) to identify four phases of the economic cycle (expansion, peak, recession and recovery). Also unlike other studies, we consider a broad opportunity set instead of focusing on the attractiveness of one particular asset class. In addition to equities, bonds and cash we include small caps, value, growth, credits and commodities in our analysis. The framework which we describe is intended to help long-term investors design a dynamic strategic asset allocation strategy over the economic cycle and can easily be extended with different economic variables and/or additional assets.

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. Besides risk, the average return of many assets is also found to be highly dependent on the economic regime. For example, most assets exhibit above-average returns during recessions and recoveries and below-average returns during expansions and peaks. We show that investors can improve the performance of their strategic asset allocation by taking into account the regime-dependent risk and return properties of each asset class. We first examine a classic tactical asset allocation (TAA) 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

[3] For example, Massimo 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. Ang and Bekaert (2004) design a strategy which 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.

systematically, and during bad times in particular. In order to address this concern we propose a dynamic strategic asset allocation (DSAA) approach which is successful at stabilizing portfolio risk across the economic cycle, whilst, at the same time, offering the potential to enhance portfolio return. We show that our empirical results are robust to changing the variables in the regime model, with considerable potential for further improvement. Finally, we argue that outsourcing a dynamic strategic asset allocation 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 regime-dependent constraints, e.g. by setting time-varying asset class bandwidths. Alternatively, investors could decide to fully integrate DSAA into their own strategic asset allocation policy.

The paper proceeds as follows. Section 2 discusses the data and methodology, followed by the empirical results in section 3. Section 4 concludes.

II. Data and methodology

2.1 Data

We consider the following eight asset classes and investment styles: U.S. large cap equities, U.S. small cap equities, U.S. value equities, U.S. growth equities, U.S. credits, U.S. Treasuries, commodities and cash.[4] All returns are in U.S. dollars. The sample period is from January 1948 through December 2007, spanning a total of 60 years. We use a monthly data frequency.

For identifying regimes we consider four well-known economic indicators for which also 60 years of data history is available.[5] The indicators consist of two market

[4] 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 onwards, and prior to 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 prior to January 1979. Credit returns are based on the Lehman U.S. Aggregate Corporate index, backfilled with data from Ibbotson (LT Corporate) prior to January 1973. U.S. Treasuries are based on the Lehman U.S. Aggregate Treasury index, backfilled with Ibbotson data (IT Government) prior to January 1973. Commodities are defined as the GSCI index, back-filled with the CRB spot index prior to January 1970. Cash is defined as the return on U.S. 30-day T-bills.

[5] For the credit spread we take the Baa-Aaa spread as defined by Moody's. The earnings yield is the E/P for the S&P500. The ISM index is defined as the U.S. manufacturers survey production index seasonally adjusted. Finally, the unemployment rate is the seasonally adjusted U.S. unemployment rate. The ISM data and unemployment data are final figures and could differ from the preliminary figures published earlier. All data are obtained from Datastream and prior to 1970 backfilled the FRED database (http://research.stlouisfed.org/fred2) and, for P/E, Robert Shiller's database (http://www.econ.yale.edu/~shill

factors and two macro factors. The market factors are the credit spread (difference between the Baa-Aaa spreads) and earnings yield (E/P ratio of the S&P500). A high credit spread or high earnings yield indicates 'contraction' and low spreads or yields indicate 'expansion'. The two macro factors are the seasonally adjusted U.S. ISM manufacturers' survey production index and the seasonally adjusted U.S. unemployment rate. An ISM value above 0.50 or low unemployment indicates 'expansion' and an ISM below 0.50 or high unemployment indicate 'contraction'.

2.2 Defining economic regimes

The NBER is well-known for determining official recessionary periods. NBER data is of little use for real-life dynamic asset allocation purposes though, because the NBER only classifies a period as either expansion or recession after the fact. Because of this hindsight, the NBER data is 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.[6]

In order to address this concern we propose an alternative, forward-looking regime indicator. Our indicator uses only information which is actually available ex ante and offers the additional advantage of resulting in a more balanced distribution of observations across regimes. In the appendix we describe in detail how we combine the four separate economic indicators described in the data section into one overall regime indicator, which can take on four different states. The four regimes are schematically illustrated in Figure 1. In the 'expansion' phase the combination of 4 economic indicators is both positive and rising. In the 'peak' phase the level is still positive, but conditions are worsening. In the 'recession' phase both level and direction are negative, while in the 'recovery' phase the level is still negative, but improving. We will refer to the expansion and peak phase as 'good times' and recession and recovery as 'bad times'.

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er/data.htm).

[6] Actually, Gorton and Rouwenhorst (2006) go even one step further by distinguishing between early and late expansions and early and late recessions, based on 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 regimes is quite unbalanced. Specifically, for our 60-year sample, early and late recessions in particular each contain only 8% of the data points, which is equivalent to fewer than 5 years of observations.

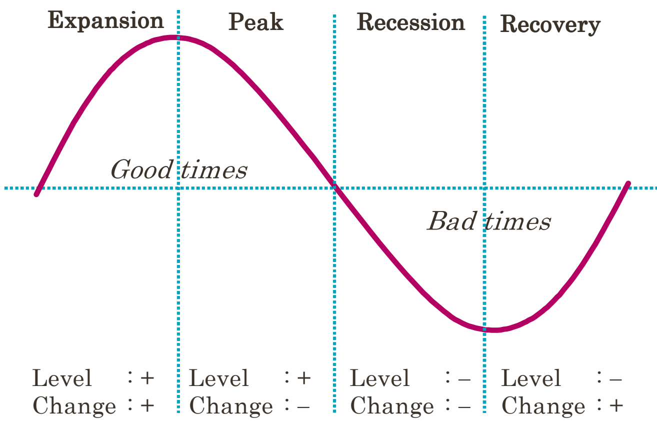

Figure 1: Economic cycle with 4 regimes

We also show that our regime indicator matches fairly well with the 'official' NBER economic cycle classification, although we fully acknowledge that our method may be improved upon with a more sophisticated approach. However, the regime indicator suffices for the purposes of this paper: to compare various dynamic strategic asset allocation approaches based on a regime framework, and to estimate the potential for risk/return improvement that is offered by regime-based approaches. Furthermore, we will show that our main results are robust to variations in the variable composition of the regime-classification model.

2.3 Asset allocation strategies

As a base case strategic asset allocation policy, we consider a static SAA portfolio which every month invests 25% in large-cap equities, 25% in Treasuries and 25% in cash (core assets) and 5% in value equities, 5% in growth equities, 5% in small-cap equities, 5% in credits and 5% in commodities (satellite assets). Next we consider several dynamic asset allocation approaches that are based on our economic regime indicator. Each alternative is based on optimizing the asset allocation for each of the four regimes separately, where for each alternative we use a different set of restrictions. An overview is given in Table 1.

	TAA	TAA-C	DSAA
Panel A: Asset weight restrictions			
Core assets	0-100%	0-100%	0-100%
Satellite assets	0-10%	0-10%	0-10%
Panel B: Relative risk constraints			
Tracking error limit	1%	1%	1%
Panel C: Absolute risk constraints			
Volatility limit full sample	-	$\sigma_{SAA\ full\ sample}$	$\sigma_{SAA\ full\ sample}$
Volatility limit for each regime	-	-	$\sigma_{SAA\ full\ sample}$

Table 1: Definition asset allocation strategies

The first alternative which we consider is a tactical asset allocation (TAA) strategy, in which we optimize the portfolio in each economic regime for maximum expected return, subject to a 1% 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 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, add to 1 and not exceed 10% for the five satellite assets.[7] Weights for the three core assets are not constrained to a maximum value.

Because 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 economic regimes we therefore consider a final alternative, which we call a dynamic strategic asset allocation strategy (DSAA). With this approach we impose the additional restriction that not only

[7] Jagannathan and Ma (2003) show that restricting portfolio weights is effectively a form of covariance matrix shrinkage. Diris, Palm and Schotman (2008) stress the importance of shrinkage when determining an asset allocation strategy.

overall portfolio volatility, but also volatility during each of the four regimes 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.[8] With the full-sample approach we have an average of 15 years of data for each of the four economic regimes, 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 (or no) remaining data for an out-of-sample test. Furthermore, as mentioned before, the primary objective of this paper is to present a framework for dynamic asset allocation, and the empirical data is only meant to illustrate the potential of such an approach. Our results do not aim to represent real-life investment strategies.

III. Results

3.1 Risk and return across regimes

We begin our empirical analysis with investigating the risk and return of the assets in our sample across the different economic regimes. Table 2 shows the correlations between several asset classes during each phase of the economic cycle. These estimates are based on monthly data, but we note that quarterly data yields 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 peaks 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 between equities and commodities becomes negative, indicating more opportunities for diversification.

[8] 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.

	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
Peak	-0.16	0.12	0.02
Recession	0.15	0.35	0.02
Recovery	0.38	0.45	-0.12

Table 2: Key correlations across different economic regimes. Sample period 1948-2007

Table 3 shows the annualized volatility of each asset class, as well as the static SAA portfolio, across the different regimes. 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%, but this number varies between 5.6% in good times and 6.6% 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 regimes in the economic cycle.

	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%
Peak	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%

Table 3: Risk of asset classes for each economic regime. Risk is defined as annualized volatility. Sample period 1948-2007

Table 4 shows the excess (log-)returns of each asset class across the four regimes. The SAA portfolio yields an average return of 2.9% in excess of cash, but this return varies between 0.5% during peaks and 4.8% during recessions. This result is driven by the fact that equity returns are highest during recessions and lowest during peaks. This suggests that financial markets run ahead of the economic cycle by about one phase. In other words, when the real economy peaks, equity markets already show disappointing returns because of the anticipated recession, while equity markets are already recovering when the real economy is still in recession. In other words, 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 risks are higher, but also returns tend to be higher.

	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%
Peak	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%

Table 4: Annualized excess return of asset classes during each economic regime. Sample period 1948-2007

Interestingly, both the value premium (value versus growth) and the size premium (small versus large) are negative during 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 peaks. Commodities deliver high returns during expansions and recoveries, whilst lagging during peaks and recessions. In sum, we observe various pronounced cyclical patterns in the premiums of the different asset classes, which further motivates the examination of regime-based asset allocation strategies.

3.2 Regime-based asset allocation

In this section we compare the static SAA approach with the regime-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.

	Equity	Value	Growth	Small	Credits	Bonds	Comm	Rf
Panel A: SAA								
Static	25%	5%	5%	5%	5%	25%	5%	25%
Panel B: TAA								
Expansion	39%		3%	2%		26%	10%	21%
Peak	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%
Peak	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%
Peak	19%	10%		10%		31%	5%	25%
Recession	20%	10%		9%		27%		34%
Recovery	18%	10%		10%	10%	19%	10%	23%

Table 5: Optimized regime-dependent allocation strategies. Sample period 1948-2007

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

Table 6: Risk and return characteristics of regime-based allocation strategies. 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

For each regime, the base-case TAA approach selects a portfolio which 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 annum, compared to 2.90% for the static SAA approach. The difference is 0.81%, which, given the tracking error budget of 1%, 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% during peak regimes to 1.08% 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 SAA reference portfolio. Compared to the static SAA portfolio, overall volatility increases from 6.17% to 6.82%, and volatility is also higher in each of the four separate economic regimes. One of the reasons for this is that the TAA portfolios systematically overweight equities and underweight cash compared to 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 performance 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% (equivalent to an information ratio of 0.61, with a t-value of 4.70), ranging from 0.43% during expansions to 0.81% during recoveries. During peaks, 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 peaks 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 regimes. 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 regimes (expansions and peaks), in order to be able to take on more risk during the highest return regime (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 behaviour. 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 which we call dynamic strategic asset allocation, or DSAA. This approach is specifically designed to stabilize risk across the economic cycle. Specifically, the portfolios are optimized subject to the constraint that not only overall volatility, but also volatility during each regime does not exceed 6.17%. Looking at the resulting portfolios, we observe that the main change compared to the TAA-C approach is the weight of equities, which is now chosen in such a way that risk across different economic regimes is stabilized. The average return enhancement is equal to 0.48%, implying an information ratio of 0.48 (with a t-value of 3.71). The return improvement ranges between 0.50% and 0.75% during expansions, peaks and recoveries. During recessions, the main improvement is not an increase in expected return (which is enhanced by only 0.17% in this regime), but a reduction of risk, as volatility can be seen to drop from 6.55% to 6.17%. Stable risk across the economic cycle is desirable for a risk-averse investor with a constant risk budget. To summarize, the DSAA approach is able to stabilize risk across economic regimes, whilst, at the same time, improving expected return.

3.3 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 requirement is likely to be most challenging. However, even if expected returns are considered to be unpredictable, there remains a case for DSAA, albeit a simplified variant which is solely aimed at stabilizing portfolio risk. In this section we will examine the robustness of our finding that, at the very least, a regime-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 regime model, we observe that the risk of each class is significantly higher during 'bad times' (NBER contractions) compared to 'good times' (NBER expansions). This provides corroborating evidence for the existence of time-varying risk that is linked to the economic cycle.

	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%

Table 7: Risk of asset classes for each economic regime. Risk is defined as annualized volatility. Sample period 1948-2007

The regime model that has been used throughout this paper 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, form the regime model. Therefore we examined the effects of leaving out any one of the four variables in the regime-model. The results of this analysis are shown in Table 8. We observe that removing any one of the four variables in the regime 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 regimes tends to widen.

Regime model sensitivity analysis						
	Base case	Excl. credit spread	Excl. earnings yield	Excl. ISM	Excl. unemploy-ment	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%

Table 8: SAA portfolio risk across the economic cycle for alternative regime models. Risk is defined as annualized volatility and return is excess return over cash. Sample period 1948-2007

If DSAA is applied with the sole objective to stabilize portfolio risk, one might consider tailoring the regime model specifically towards that purpose. Empirically volatility is often found to be persistent, i.e. if volatility has recently been high (low), it is likely to remain high (low) in the following period. The literature which takes a purely statistical approach towards 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 regime model.[9] 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 regime 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 regimes

[9] A forward-looking implied volatility indicator such as VIX might be even more appealing, but the data for such variables is not available with a history of sixty years.

increases from less than 1% to over 1.5%.[10] We conclude that, if the primary objective of a regime approach is considered to be stabilizing portfolio risk over time, our base-case regime model does not paint an overly optimistic picture, as we find that even stronger results may be obtained by considering additional variables.

IV. Summary and implications

We propose a practical investment framework for dynamic asset allocation across economic regimes, which we illustrate with a sample of data for the U.S. market over the period from 1948 until 2007. We define an economic regime indicator based on a combination of four well-known economic variables, which can take on four different states. The regime indicator is found to relate reasonably well to the official NBER economic cycle. Our first empirical result is that the risk and return properties of asset classes are highly dependent on the prevailing economic regime. Using this insight we examine various regime-based asset allocation strategies. The benchmark is an SAA portfolio with static weights, but with a time-varying risk profile across the economic cycle. In particular, risk tends to go up in bad times, which is undesirable for a risk-averse investor. One way investors can exploit economic regimes is by developing a TAA strategy, which is designed for a maximum outperformance in each economic regime. 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. For investors who are sceptical towards 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 economic regimes 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, while relative return investors increase risk during bad times. These opposing outcomes

[10] This spread even widens to over 2% if the volatility factor is added twice, i.e. not only as a fifth but also as a sixth variable in the regime model.

imply that it is essential to clearly specify the investment objectives, consistent with the finding by Binsbergen, Koijen and Brandt (2009) that a decentralized investment approach can lead to suboptimal portfolios.

Institutional investors who would like to implement a regime-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 which concentrates on maximizing returns can have undesired consequences for the overall risk profile of the portfolio. A DSAA strategy with overall and regime-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 if 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 regime-dependent constraints (e.g. bandwidths) on the exposure to each asset class. For example, in case a high-risk regime is identified, a TAA manager might be restricted from overweighting high-risk assets such as equities

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Appendix: Construction of economic regime indicator

Figure A.1 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 50-125 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 onwards. The earnings yield can be described in four phases. It varies between 8-16% from 1948-1958, falling to 4-8% during 1959-1973, going up again to 8-15% during the 1973-1985 period, and then varying between 2-8% 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% about 15 times. Thus the different cycles last between 2-20 years, depending on the variable under consideration.

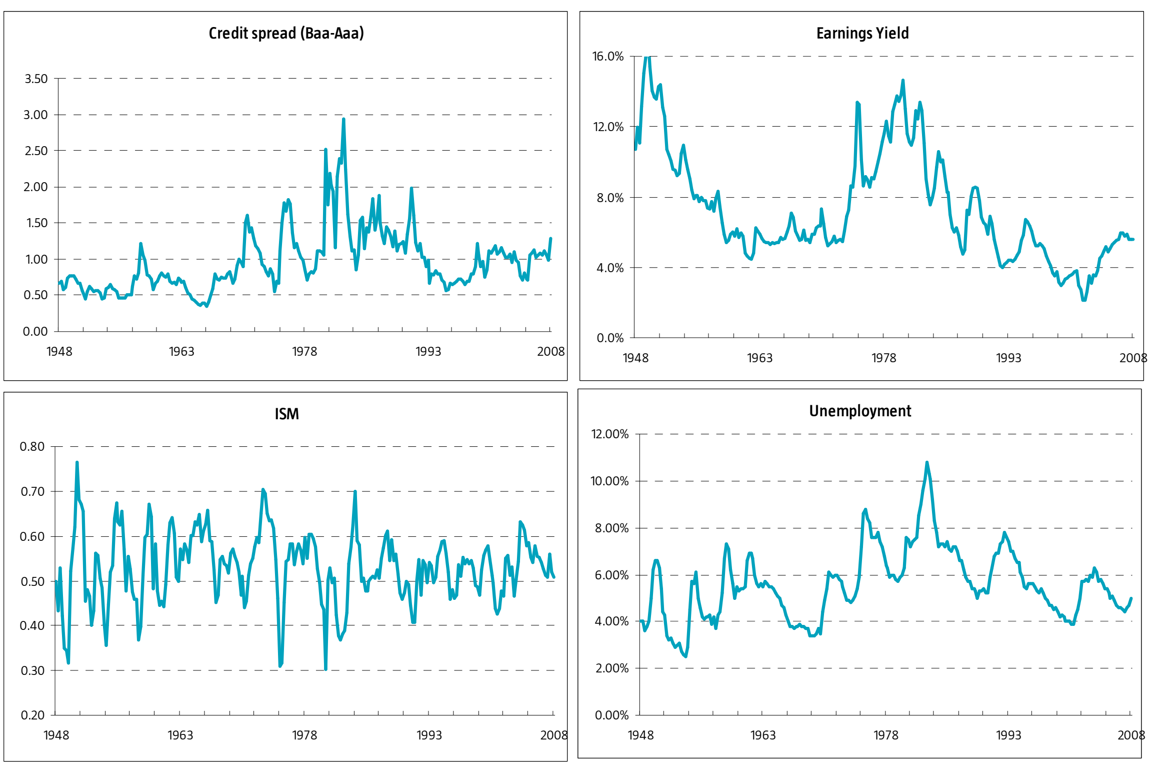

Figure A.1: Time-series of each conditioning variable. Monthly observations over the 60 year period 1948-2007

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% of all observations.[11] It is important to note that NBER classifies a contraction with hindsight, while our regime indicator only uses information available prior to the next month. Table A.1 shows the average level and 1-year change of each indicator during the full sample and during NBER recession periods.

	Full sample		NBER Contractions	
	Level	Stdev.	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

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

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 to 1.0 standard deviations from their long-term average values.

In order to obtain a robust and broad indication of the condition of the U.S. economy, we proceed by combining the four economic factors into one overall regime score.[12] We note that the main findings in this paper are robust to leaving out any one of the four indicators. We standardize the four economic variables by deducting their full-sample medians[13] and 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

[11] http://www.nber.org/cycles.html
[12] 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.
[13] We use median instead of mean in order to reduce the impact of outliers on the resulting z-scores.

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.[14]

Based on the combined indicator we define four economic phases or regimes. In the 'expansion' phase the combined indicator is both positive and increasing. In the 'peak' phase the level is still positive, but conditions are worsening. In the 'recession' phase both level and direction are negative, while 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 peak and through data. However, the advantages of our approach are that (i) it is applicable in practice as the required data is readily available ex ante and (ii) the monthly observations are more evenly distributed across regimes leading to more statistical power.

Figure A.2 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', while 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 A.1.

We translate the combined economic indicator into four regimes or 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.

[14] 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.

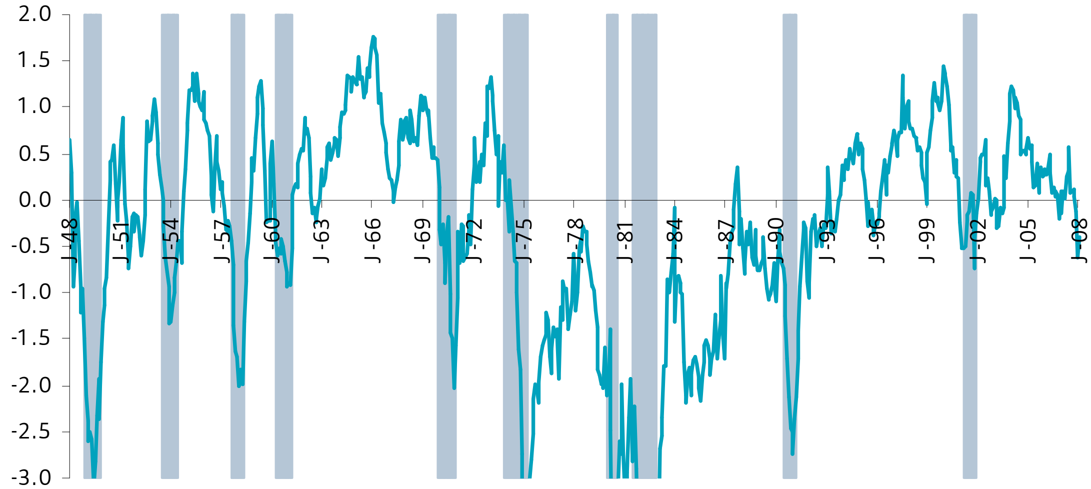

Figure A.2: Time-series of the combined economic indicator combined with NBER contraction periods. Monthly observations over the 60-year period 1948-2007

Table A.2 shows the distribution of the four economic regimes and the accompanying transition matrix. The expansion and recession regimes occur more often than peak and recovery regimes. 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 peaks in particular to be rather short-lived. The transition matrix shows that the probability of staying in one regime from month to month is between 83-93%, while the probability of moving to another regime is 7-17%. This translates into an average duration of each phase in the economic cycle of about 9 months. [15]

[15] In order to limit the transition of one phase to another due to 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 regime and keep the same regime as in the previous month. The same threshold applies for 1-year changes which should also exceed an absolute value of 0.10.

			Transition Matrix			
Total #	NBER	From/To	Expansion	Peak	Recession	Recovery
230	1	Expansion	93%	3%	-	3%
95	6	Peak	6%	83%	11%	-
238	101	Recession	2%	3%	90%	4%
144	6	Recovery	4%	-	8%	88%

Table A.2: Distribution of 4 economic regimes and transition matrix

When our regime model indicates a state of recession, there is a 42% chance that NBER will later on classify this month as a part of a contraction period. We find that 90% of all NBER contraction periods fall within the model recession phase, while 10% falls in either peak 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 peak (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 which can be used to translate economic variables into a regime indicator which can take on four different states. With the four variables proposed in this paper, the regime indicator is found to match reasonably well with the official economic cycle as reported by the NBER.