A comparison of non-parametric and parametric style timing strategies

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Abstract

Several brokers believe that style timing strategies based on macro-economic indicator series could yield better returns. I test three of these broker models to see if their rule based style timing methods pay off on the European market. Furthermore, I construct my own style timing model based on a Markov switching vector autoregressive model. The models are tested on ten different styles consisting of European stocks. I find that some styles perform better when being timed and that a simple rule based model yields higher returns for the period 2001-2016 than a more complex parametric model. The MS-VAR model has identification problems due to lack of recession data and the added value of the Markov switching property of the model parameters is minimal.

Keywords: Business cycles; Markov switching; Style timing; European markets.

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Contents

1 Introduction

The economy follows a pattern of expansion and recession. The existence of this cyclical behavior is widely accepted. It is common practice to divide the macro-economic cycle in four main stages or regimes: Expansion, Downturn, Recession, and Recovery. Each stage has its own properties with respect to the state of the macro-economy and its growth. It is tempting to assume that during certain economic regimes certain trading styles are more attractive than others. One can easily imagine that traders would value quality stocks or low-risk stocks more during recessions and growth stocks during expansion periods. However, the significance of returns based on these 'style timing'-strategies and via which methodology the optimal switching moment can be identified are subject to debate.

For decades investors and researchers have been investigating whether active style timing strategies can generate higher returns by taking style timing into account. They argue that style based investment strategies do not perform constantly over time but are time-varying, depending on the economic regime. If an investor wants to successfully put such a strategy into practice, it is very important to correctly identify and forecast the macro-economic regime. However, there is no consensus on the identification methodology of the macro-economic cycle and much research is done into this subject. Two main schools with respect to this identification and forecasting exist: parametric models and non-parametric models. The latter uses no statistical model to date turning points in the economy but instead uses a dating algorithm based on macro-economic data series. The former fits a statistical model to the data and then uses the estimated model to define turning point dates.

The choice of style timing based on the business cycle rather than the stock market cycle also needs argumentation. There are indications that style timing based on the macro-economy is not the best choice. Some researchers argue that macro-economic based style timing is not profitable and that it is better to look at the stock market cycle directly. Estrella and Mishkin [1998] even find that the stock market cycle leads the macro-economic cycle and not the other way around. There are also discrepancies between both cycles such as the tech bubble, which was not classified as a macro-economic recession while it had great influence on stock market returns. This thesis however only considers macro input and no stock market information. Main argumentation being that the client company wants to know whether it is profitable to slightly tilt weights of certain styles based on macro-economic regime.

This thesis aims to construct a parametric model for the Eurozone macro-economic cycle which improves the style timing performance of non-parametric based models used by several brokers. Many brokers have some sort of model which tries to identify the current macro-economic state and they alter their style allocation based on what their macro indicator tells them. These models are fairly simple and rely heavily on expert judgement rather than objective input from available data. This thesis therefore aims to construct a more objective model which uses actual data input for investment decisions rather than subjective expert judgement. An expert bases his or her investments under influence of sentiment or hunches which could lead to wrong decisions. Whereas, an objective model only uses the actual presented information which thus could yield better results.

In order to evaluate the performance of the parametric investment model, it tries to beat the Eurozone macro-economic indicator models of three different brokers: Bank of America Merrill Lynch, J.P. Morgan, and Nomura. These non-parametric broker models merely indicate the economy while leaving investment decisions to an expert. I use a Markov switching vector autoregressive model (MS-VAR) as the parametric model to capture and forecast the economic regime of the Eurozone. This non-linear model can be extended to incorporate several properties and can thus capture some important market features.

The broker models all divide the economy into four possible macro-economic stages: Expansion, Downturn, Recession, and Recovery. For each of these stages a different style allocation is picked based on past style performance in each regime. For the trading strategy I review style returns from ten different styles. Each month every style gets a investment weight (negative weight imply a short position in the style) which depends on the styles mean, variance, and a risk aversion parameter. In case of the broker models this is done based on the mean return of the style and its variance in each regime.

In contrast with the broker models, the MS-VAR model divides the economy in only two possible states, expansion or recession. Investment decision for each style depends on the styles expected return and the styles expected variance. They are both constructed by weighing the regime dependant expected values by probabilities of the economic regimes the next month.

A Markov switching model is a model subjected to switching parameters as first proposed by Hamilton [1989]. The parameters of the model can be in one of two states, expansion or recession. While the real state of the economy remains latent or unobservable, the model infers for each month the probability of being in a recession. The economic regime follows a first-order Markov chain of which the transition probabilities are based on the input data. An often mentioned property of the business cycle is its asymmetry, in the sense that contractions are more violent but have a shorter duration than expansions. Assuming this is indeed true, it makes sense to apply a model with different parameters sets for these different economic regimes. The economic regime switching driven by a Markov process allows for this asymmetry.

The combination of the Markov switching model and the VAR model is first extensively used and described by Krolzig [2003a]. Advantage of this model is the possibility to link multiple indicators with different leads and lags; although all are subjected to the same underlying switching regimes. Furthermore, as is the case with the regular Markov switching model, this MS-VAR model can be adapted in a lot of ways to capture different economic and market effects.

Based on the literature, which I review in the next chapter, I decide to construct an MS-VAR model for the Eurozone which allows for two different economic states and varying lead times for different leading indicators. Furthermore, I allow regime based heteroskedasticity, since style return movement tends to vary more during recession than during expansion phases.

Several problems arise around practical implementation of a strategy based on the hypothesis that style timing pays off. The first being that the macro-economy needs to be identified. Secondly it needs to be predicted with a reasonable amount of accuracy. Then there is also the question which styles perform best in which macro-economic regimes and which styles exhibit rotation behaviour at all. This research focuses mostly on the first three problems. The last is only addressed partly since I pick certain styles beforehand and do not consider a broad list of styles to see which perform best in what regime.

This research is done solely for the Eurozone market because a lot of research is already done for the US markets. Since (new) methodologies are not always applied outside the US, a change of input data contributes in testing whether results found in there are also applicable to the Eurozone. Another difference with other research regarding this subject is the more direct practical way in which I measure the performance. I do this by comparing returns on a predefined trading strategy based on style portfolios constructed from European financial products.

First I assess the identification performance in-sample by comparing the peaks and through dates given by the models to the official Eurozone economic ones given by the Euro Area Business Cycle Dating Committee. Then I measure the out-of-sample performance of all models by comparing style timing strategy returns. These strategies aim to calculate investment weights for ten different styles in different ways. I incorporate fixed transaction costs every time the weights are rebalanced. Furthermore I compare both the broker models and the MS-VAR model to a regular VAR model and a buy-and-hold strategy.

From the broker research I find that none of them perform better than the buy-and-hold benchmark in terms of the Sharpe ratio but all do in terms of mean return. When looking at the individual styles only Book-to-Price improves in terms of the Sharpe ratio when style timing is included in the model.

Both the MS-VAR and VAR perform better than one of the three brokers in terms of the total strategy return and better than all three with respect to the strategies Sharpe ratio, 0.52 to 0.44, 0.50, and 0.45. The buy-and-hold benchmark with Sharpe ratios of 0.53 has the best performance mainly thank to the low volatility. Over the out-of-sample period of 2001 to 2016 the total strategy return of the best performing broker, JPM, is the highest 163%. While the MS-VAR, VAR, and the buy-and-hold follow with 150%, 149%, and 141% respectively. This indicates that including the information from the macro-economic indicators in the model to establish weights for the next month, and thus style timing, pays off. Although a margin of 10% in 15 years is not much. Tests for the strategy returns show that the differences of the Sharpe ratios are not significantly different from 0. Comparing the VAR results with the MS-VAR I find that the performance is highly alike. On average only 1% over the entire 15 years is gained by allowing for Markov-switching in the parameters. Too little to be convincing, although better performance could be expected if applied to a longer time series since overfitting problems of the MS-VAR are likely to disappear.

My results imply that parametric models I tried, the VAR and MS-VAR model, do not improve the simple rule based style timing models that brokers use for timing the Eurozone economy. They do with respect to the Sharpe ratio by lowering volatility but have a lower mean return. When looking at the Sharpe ratio none of the style timing strategies improve upon the buy-and-hold but all do in term of the total strategy return.

The remainder of this report starts with a literature review in Chapter 2 and then, in Chapter 3 a description of the data used for the research. In Chapter 4 the methodology of this research is explained, whereas Chapter 5 describes and interpret the results. In Chapter 6 I draw conclusions and discuss recommendations for further research.

2 Literature Review

The concept of style rotation has been the subject of research for a long time. Whether it can generate excess returns is disputed constantly. Lucas et al. [2002] find that 'firm-specific characteristics like size and book-to-price on future excess stock returns varies considerably over time'. They find significant returns for style timing based strategies and get the best result for business cycle oriented approaches. Chan et al. [2000] show that the size and value effect are inverted from 1990 to 1998. Which implies style timing is an effect to incorporate in multi-year investment strategies. From a more practical view of point Roll [1992] argues that professional money managers are assessed on both yearly outperformance as well as intra-year variability of the outperformance. Managers are looking for systematic patterns in the time-varying impact of value and size on returns. The cause of these fluctuations could lie in macro-economic variation. In practice style timing is thus being used.

Others argue the style timing effects disappear when certain aspects are included in the models. Wang [2005] argues that the measures used to assess style timing are problematic in evaluating style timing and proposes a new weight approach. He finds that the conventional methods lead to misleading results and that the Fama and French's 3-factor model can account for style timing performance.

Estrella and Mishkin [1998] argue that forecasting with macro-economic models is better used for understanding the economy rather than usage for trading strategies or recession prediction. They even find that stock prices (and yield curve spread) play a useful role in predicting the macro-economy and not the other way around. Style timing is thus useful only not with macro-economic indicators.

The first to use a Markov switching specification to describe the non-linearity of the economic cycle is Hamilton [1989]. He uses real US GNP growth and finds that the cycle is best described by a latent variable which put the economy in a growth state or in a recessionary state. He estimates this non-linear model by means of maximum likelihood, but because of the non-linearity the standard tests cannot be applied to test outcomes. Hansen [1992], however develops a test in this framework which can be applied to this model. It is a likelihood ratio statistic which tests the null hypothesis of linearity against the alternative of an MS model. It can thus be used to check if individual indicators are indeed subjected to regime switches.

The MS model can be altered in several ways to allow for different model properties. Durland and McCurdy [1994] allow regime transition probabilities to be time varying and duration dependent and they reject the MS model with time constant probabilities for the US cycle. Kim and Yoo [1995] are the first to extent the MS model of Hamilton [1989] to a multivariate MS model with coincident economic indicators and also allow regime transition probabilities to be time varying but in addition make them dependent on conditioning information coming from the indicators. They find that this time varying matters in the postwar US business cycle.

Another interesting extension to the model is made by Sichel [1994], he introduces a third state which allows for a stronger expansion regime. Kim et al. [2002] make this third regime dependent on the duration of the previous recession. Both papers find the addition of this state is improving the model for the US business cycle. Artis et al. [2004] however, finds that this third state is not present in the European cycle and I will therefore not investigate this application in this research.

The first one to extensively use an MS-VAR model to describe the business cycle is Krolzig [2003a] and uses it to forecast the US GNP and employment growth. He finds that the MS-VAR can improve short horizon predictions but that forecastablility requires absence of structural breaks in regime shift patterns. Krolzig [2003b] applies the MS-VAR model to construct turning points in the Eurozone business cycle and find that the presence of a common Markovian Eurozone business cycle is very robust.

The MS-VAR can incorporate the same features as the univariate MS model. Chauvet and Hamilton [2006] use the MS-VAR to incorporate four coincident economic variables to infer the state of the business cycle. Hamilton and Perez-Quiros [1996] use the MS-VAR framework to give a composite leading indicator a positive lag compared to the main cycle and find that useful composite leading indicator exists for the US GNP. Paap et al. [2007] go even further and allow the leading lag for peaks to differ from the leading lag for troughs. They conclude that allowing for this lag difference is a useful model specification. Also out-of-sample forecasts improve by allowing for asymmetric lead times.

Another application of the Markov regime switching models based on Hamilton [1989] is in equity markets directly. Maheu and McCurdy [2000] take the Durland and McCurdy [1994] model as a basis and extend it in order to investigate duration dependence of market states as a source of non-linearity in the stock market cycle. They make the mean and variance of regimes duration dependent. The model furthermore captures ARCH effects.

Kole and van Dijk [2016] compare semi-parametric and parametric (MSM) models via the mean-variance utilities of a risk averse agent. They find that the MSM has better out-of-sample performance. They also use the variance of the stock market to indicate the state, which has very good results. With respect to the Markov switching model the best performing variant uses a two regime (bear and bull) model with time varying transition probabilities, and with regime specific means and variances. They implement the time varying information from predictor variables for the transition probabilities via a logit specification.

3 Data

The data I use can roughly be divided in four types. The indicator data used as input for the broker models, the indicator data for the MS-VAR model, the CEPR peak and trough dates, and the equity style returns used for the trading strategy and thus for model performance measuring. Summary statistics and availability of the time series are presented here. Other specifics of the data like sample start, sample end, sources, and time series graphs can be found in Appendix A. All data is available monthly and for some series even daily. Since I conduct this research with mostly monthly data I pick the months-end value of the daily time series as input for the models. As can be seen in the Appendix some variables have some publication lags compared to each other and to the present time. For now this problem will be ignored.

3.1 Broker data

I examine three broker models, Bank of America Merrill Lynch, J.P.Morgan, and Nomura, to which I will respectively refer to as broker BAML, JPM, and Nomura. BAML uses five coincident indicators as input for their Eurozone macro-economic indicator, namely:

1. 12 Month change in OECD Composite Leading Indicator (CLI)

2. 12 Month change in EU bond yield (Germany, France, UK)

3. German IFO indicator

4. Pan European 12 month change in Producer Price Inflation

5. 2 Month Global Sell-Side EPS revisions ratio

Pan indicates that other developed EU countries as the UK, Switzerland and Norway are included in the indicator. The broker gives no further argumentation as to why these indicators are selected or the selection procedure. Also note that these are all used as coincident variables rather than leading ones. The summary statistics and availability lag can be found in Table 1a. It can be seen that the PPI and EPS have the largest lag, one month and one day. The bond yield and the IFO are available at months-end and the CLI two weeks after months-end. Since these are the exact input series for the broker models, the brokers publish their indicators with a lag of two months. During this research I do not consider this practical obstruction.

JPM uses six indicators:

1. 12 Month change in M1 Eurozone money supply

2. 6 Month change OECD Composite Leading Indicator

3. 12 Month change in EU bond yield (Germany, France, UK)

4. German IFO indicator

5. Swedish Krona to US Dollar exchange rate

6. 2 Month Global Sell-Side EPS revisions ratio

There are only two differences with respect to BAML: the PPI change have been replaced by the M1 money supply and the Swedish Krona to US Dollar exchange rate. Furthermore they use the 6 month difference in the CLI indicator instead of the 12 month differences. They also give no further argumentation as to why these indicators are selected or clarify a selection procedure. Also note that these are all used as coincident variables well. In Table 1b with summary statistics and lag data it can be seen that again the EPS revisions has the biggest lag compared to the month it revers to. The SEK/USD is instantly available since it is a daily series.

	CLI 12m-%	Bond Yield 12m-%	IFO	EPS rev	PPI 12m-%
Mean	0.056	-2.195	101.615	-0.013	1.654
Std	1.488	14.600	6.851	0.072	2.653
Lag (days)	13	1	-5	32	32

(a) Summary statistics BAML series

	CLI 6 m-%	Bond Yield 12m-%	IFO	EPS rev	M1 12m-	USD/SEK%
Mean	0.019	-2.195	101.615	-0.013	7.692	0.159
Std	0.802	14.600	6.851	0.072	3.160	0.041
Lag (days)	13	1	-5	32	27	0

(b) Summary statistics JPM series

	Real GDP growth-12m-%	ESI
Mean	1.446	100.661
Std	1.926	9.556
Lag (days)	92	-3

(c) Summary statistics Nomura series

(d) Summary statistics input series broker models

Note: Lag is in calendar days compared to the last day of the month it refers to. For example, the CLI is published the 13th of the next month. Most series are not published in the weekend or on holidays and the number of days is therefore an indication.

Nomura has a different model setting than the first two and only uses two time series in its analysis. The summary statistics of these two series, the Eurozone GDP and the European Sentiment Indicator from the European Commission, are shown in Table 1c. This ESI has no publication lag since it is published the 27th of the same month it refers to.

With respect to the broker models, the most recently started input series is that of the Earnings per Share revisions indicator starting in December 1993, see Appendix A. Furthermore the return data used further on also start at this date. This gives 267 data points if the time series is taken to February 2016.

3.2 MS-VAR data

The MS-VAR model uses a different set of time series some of which have to be selected for actual model use based on the first analyses. For the coincident and leading indicators I pick several series as candidates based on the literature. One of the most promising is the Composite Leading Indicator of the Eurozone as constructed by the OECD. It is constructed as a weighted average of the CLI's of the countries: Austria, Belgium, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Slovak Republic, Slovenia, and Spain. Each of these individual countries has five or six different underlying indicators for their CLI which are deemed of importance for that particular economy. Based on literature and the broker reports I examine the following other leading indicators and/or coincident indicators.

Potential indicators

1. Composite Leading Indicator of the Eurozone
2. Economic Sentiment Indicator (European Commission)
3. Index of Housing Permits Granted measured in square meters (Eurostat)
4. Eurostoxx stock price index (Dow Jones)

5. 12 month change of European Central Bank (ECB) monetary aggregate (M2) for the euro area (deflated using a consumer price index) (Eurostat)
6. Index of Industrial Production of the EU (IIP)
7. 12 month change in EU bond yield
8. Swedish Krona - US Dollar exchange rate (SEK/USD)
9. 12 month change of M1 Eurozone money supply
10. 2 month global Sell-Side EPS revisions

First, all potential indicator series should be stationary. Therefore they are checked for unit roots. This is done with the Augmented Dickey-Fuller test where the number of lags is set to one since it is the maximum lag I consider. The test is done three times. First a regular ADF test, then on with a deterministic intercept included and then one with a time trend included. If a series appears to be $I(1)$ the first difference of this series is taken. The resulting p-values for the presence of a unit root are show in Table 2.

Indicator	IIP	Bond Yield 12m-%	USD/SEK	M1 12m-%	EPS rev
Mean	0.1191	-2.009	-0.0517	0.8477	-0.0133
Std	1.1067	14.555	2.4962	13.3644	0.0715
Lag (days)	45	0	0	27	32
ADF	0.993	0.000	0.324	0.105	0.000
ADF + d.i.	0.520	0.000	0.412	0.000	0.000
ADF + t.s.	0.731	0.000	0.394	0.000	0.001

Indicator	CLI	ESI	Housing	Eurostoxx	M2 12m-%
Mean	0.0029	0.0340	0.0140	0.4503	0.3398
Std	0.1686	1.7023	7.0096	4.5806	9.8978
Lag (days)	13	-3	122	0	30
ADF p-value	0.570	0.625	0.357	0.670	0.185
ADF + d.i.	0.000	0.054	0.805	0.451	0.108
ADF + t.s.	0.000	0.153	0.800	0.553	0.273

Table 2: Summary statistics MS-VAR indicators and P-values ADF tests (normal, with deterministic intercept and with trend stationarity)

Note: If the unit root can't be rejected at a 5% significance level the first difference of that time series is taken. Lag is in calendar days compared to the last day of the month it revers to. Most series are not published in the weekend or on holidays and the number of days is therefore an indication.

If no intercept and trend are included in the test regression a unit root cannot be rejected for all time series with the exemption of the Bond yield (already differenced year on year) and earnings per share revisions. If these are included the unit root is also rejected for CLI and the yearly change in M1 money supply. I however follow on the choices of the brokers to take the change of the CLI as an indicator rather than the absolute value. Also the M1 money supply is differenced one more time based on the remarks by Franses et al. [2014] that money supply variables often need to be differenced twice, although here there is no numerical indication that the yearly change has a unit root when an intercept and trend are taken into account. The presented summary statistics in Table 2 are from the first difference series (month on month change) with exemption of the 12 month change in bond yield and the EPS revisions.

Furthermore all potential indicators are checked for the presence of regime switching behavior against a linear AR process, via the procedure as proposed by Hansen [1992], which is explained further in Chapter 4. Figure 1 shows the correlations and autocorrelations of the indicator series (after difference is taken). Money supplies are mainly negatively correlated with the other parameters. Housing is has overall low correlation to all other indicators and has a negative autocorrelation. Bond yield, Earnings per Share and the Composite Leading Indicator show very high autocorrelations which makes sense when taking a look at the graphs of the series in Appendix A.3.

	IIP	*BOND*	*SEK*	*M1*	*EPS*	*CLI*	*ESI*	*Hous*	*ESX*	*M2*
IIP	0,013									
BOND	0,092	0,935								
SEK	0,139	0,097	0,340							
M1	-0,205	-0,268	-0,311	0,487						
EPS	0,461	0,285	0,223	-0,377	0,923					
CLI	0,416	0,063	0,257	-0,244	0,565	0,970				
ESI	0,339	0,090	0,229	-0,223	0,506	0,766	0,534			
Hous	0,116	-0,022	-0,014	0,055	0,055	0,089	0,092	-0,350		
ESX	0,201	-0,060	0,148	-0,116	0,215	0,401	0,435	-0,022	0,293	
M2	0,069	-0,269	-0,124	0,253	-0,083	-0,198	-0,200	-0,042	0,027	0,076

Figure 1: Correlation of indicators. Values on the diagonal are the 1-month lag autocorrelations

When the models are used for forecast purposes a new problem arises. Irregular missing of data at the end of the sample occurs since not all indicator series are published instantly but with lags up to three months. For series that lead the macro-economic cycle with a lag larger than the publication lag this is not an issue of course, but for some series this is not the case. For the final model this data availability is a problem for the EPS revisions and the IIP series. Although I choose to ignore it for this research, for the practical implementation of the model a solution needs to be presented. This could be done in the form of a Kalman filter or take the value of one month earlier. The last option might yield different results especially due to the shifting of the IIP series. The consequences of the shifted EPS series is likely to be very small since the one month autocorrelation of the EPS is close to one.

3.3 Business cycle dates

To define the 'true' peaks and troughs in the economic cycle I use the dates as given by the Euro Area Business Cycle Dating Committee from the Centre for Economic Policy Research (CEPR), a European equivalent of the NBER which dates the peaks and troughs of the US economy. They compute these dates mainly based on Euro area GDP but also quarterly employment, monthly industrial production, quarterly business investment, and consumption. They indicated five complete cycles since 1974 of which the last three can be used to verify the MS-VAR model and the broker model performance. Important to notice is that the tech bubble collapse in the early 2000s is not marked as a macro-economic trough.

3.4 Market return data

Last data type are style returns from the European equity market. The source of this data is the client company, Saemor Capital and the exact underlying data is thus classified. I therefore also do not know if styles were not traded during some period. The monthly data handed over by the company does not reveal any gaps however. They consider ten different style returns constructed out of a universe of 800 different large European companies and thus so will I. I should stress that this universe also includes non-Euro countries like the UK, Norway, and Switzerland. These time series are all available from December 1993 up until now. All styles are constructed in such a way that they are long-short neutral portfolios. Shorting the worst performing companies for that style and going long in the best performing ones. The styles I consider and corresponding summary statistics are presented in Table 3. The correlation matrix is depicted in Figure 2.

Portfolio style	Mean (%)	Std (%)
Earnings yield	0.877	2.257
Book to Price ratio	0.181	3.009
Dividend yield	0.675	2.393
Free cash flow	0.787	1.505
Analyst revisions	0.920	1.784
12 month Price Momentum	1.121	4.003
Return on Equity	0.538	2.006
Debt to Assets	0.075	1.453
Market Beta	0.251	5.647
Market Capitalization	0.099	2.552

Table 3: Summary statistics of style return series

	E/P	*B/P*	*D/P*	*FCF*	*A.Rev*	*P.Mom*	*RoE*	*Dept/Ass*	*Beta*	*Size*
E/P	0,287									
B/P	0,201	0,301								
D/P	0,795	0,077	0,301							
FCF	0,318	0,142	0,326	0,158						
A.Rev	0,220	-0,545	0,184	0,151	0,078					
P.Mom	0,017	-0,688	-0,001	0,001	0,639	0,261				
RoE	0,552	-0,520	0,480	0,070	0,439	0,299	0,191			
Dept/Ass	-0,121	-0,528	-0,109	0,006	0,322	0,253	0,306	0,206		
Beta	0,508	-0,293	0,624	0,248	0,502	0,427	0,480	0,061	0,122	
Size	-0,121	0,011	-0,170	-0,280	-0,027	0,097	-0,177	-0,068	0,169	0,048

Figure 2: Correlation of return series. Values on the diagonal are the 1-month lag autocorrelations

Table 3 shows that all styles have on average positive returns, although large differences occur. It also shows that the Market Beta and Price Momentum are more volatile than the other styles. Figure 2 shows Book-to-Price ratio is negatively correlated with half of the other styles. Also Earnings-to-Price and Dividend-to-Price are strongly correlated as are Analyst Reviews and Price Momentum. Both are explainable since companies with large earnings tend to issue higher dividend. Furthermore, analysts apparently include the Price Momentum of stocks in their revisions. A high correlation with 5 different styles is visible indicating these style scores are important company/stock characteristics to analysts.

4 Methodology

In this research I compare three broker models to the MS-VAR model with respect to their capability to identify and forecast the Eurozone macro-economy. First I compare their in-sample performance in indicating peaks and troughs of the Eurozone economy. The in-sample assessment is done in the period from December 1993 until December 2015.

Then I test their performance out-of-sample, though I must stress that all three brokers explicitly indicate that their model is not made for forecasting. If that is indeed the case, the MS-VAR model should beat all other three models with respect to out-of-sample forecasts. The one-step-ahead forecasts for the broker models are given by the economic state of this month, while the MS-VAR uses indicator functions and regime switches to do a weighted forecast of the regime next month. I explain the construction of the broker models and their out-of-sample methodology first. Then I describe the MS-VAR model and the construction of the MS-VAR.

4.1 Broker models

4.1.1 Model structures

Bank of America Merrill Lynch (2016)

The methodology they use to aggregate the in Chapter 3 mentioned indicators series to one composite indicator is done by gathering the data at months end and, after normalization, aggregate data using and equal-weight average. The result is what they call a Composite Macro Indicator or CMI.

Interpretation of this constructed CMI is as follows. For each point in time they record the value of the CMI and the month on month change of the CMI ($CMI_t - CMI_{t-1}$). If the CMI is positive the economy is either in expansion or downturn. If the monthly change is also positive the economy is in expansion and if it's negative the economy is in downturn. If both the CMI and its change are negative, the European economy is in recession. Finally the recovery regime, acting if only the CMI is negative and the change is positive. In that way the entire sample from $t = 1$ up to $t = T$ can be categorized in one of these four regimes. After identification of the economic state this broker evaluate the following styles for investment: Value, Growth, Momentum, Quality, Risk and Size. However, I will evaluate the indicator for the ten styles mentioned in the previous chapter.

J.P.Morgan (2015)

JPM does not aggregate their indicators in any way as they evaluate their six indicators individually and then make an 'expert' decision on which styles to invest in. They link performance of their cycle identification variables directly to style allocation and excess return. JPM evaluates the following styles for investment: Value, Growth, Momentum, Quality, Risk, Size and Sentiment and compare monthly excess returns of each investment style per period of the economic cycle. In order to compare the brokers and the MS-VAR model I apply the same aggregation and indication method for the six variables as described for BAML.

Nomura (2015)

The third broker has a different approach in indicating the Eurozone economy. They use the monthly and instant available Economic Sentiment Index (ESI) as published by the European Commission. The ESI consists out of the following five sector sentiments with their weightings:

1. Industry 40%
2. Services 30%
3. Consumers 20%
4. Construction 5%
5. Retail trade 5%

To construct their economy cycle proxy (monthly GDP) they first regress the year on year GDP growth for each quarter on the ESI. After estimation they construct a fitted monthly GDP series. In order to establish the economic indicator (GDP growth) they use a 3-month moving average of the ESI. Then they use the change in the 3-month moving average and define that as 'momentum'. Based on these two dimensions of momentum and growth they position the economy in one of the four states. If growth and momentum are positive the economy is said to be in the expansion phase. If momentum turns negative but growth is still positive, the economy is in the downturn regime. If the the growth and the momentum become negative a recessionary state is defined. Finally when the growth is still negative, but momentum changed to positive, the recovery phase is signaled.

For all three brokers I then smooth the regimes to remove regimes which last only one month, which happens when the indicator is fluctuating around 0 or the growth is fluctuating around zero. Only regimes which last longer than 2 months are registered as a switch. As a consequence there is an extra lag in the switch from one regime into another, at least out-of-sample. Switching the investment holding one month later can generate unnecessary financial losses. However, the transaction costs induced by quickly varying regimes are likely to be higher.

4.1.2 In-sample performance

To compare how well the different models can identify actual economic cycles I compare their produced peak and trough dates with that of the Euro Area Business Cycle Dating Committee of the Centre of Economic Policy Research (CEPR). First, a rule needs to be defined for the broker models to define when a recession is indeed occurring. Since one drop in the indicator does not necessarily mean that a recession is happening. Based on the construction of the indicator of Nomura, I define a recession if the 3-month moving average is negative. If it becomes positive again the recession and recovery are over and the expansion phase begins. For the BAML and JPM indicators the principle is the same: A peak date is defined as the moment the CMI of a broker indicator becomes negative. A trough is defined as the month wherein the CMI becomes positive again and the expansion phase starts. The economic states are then smoothed again in a way that only regimes which last longer than 2 months are registered. This setup can generate a small lag in the dating of the turning points. However, the reference peak and trough dates of the CEPR committee are given per quarter rather than month, so these dates are also subjected to the same lag.

4.1.3 Out-of-sample performance

Although it is important to know whether a model can indicate the economic states in the past, the aim of the models is to indicate the economic state real time or 1-month ahead. The broker models were constructed with the sole purpose of identifying the economy real time and not to do predictions. Despite this, I still use the broker models as a benchmark for the MS-VAR model for the one-step-ahead forecasts. For these forecasts I split the time series data into two parts. The first one-third is used to estimate the model parameters while the last two-third is used to actually do the 1-month ahead forecasts.

This measure is used to see whether the models can be profitable if one actively applies style trading strategies based on the indicator. I invest in ten different style portfolios which consist out of long-short neutral portfolios. The investment weights per style vary in different states of the macro-economic cycle. The total return of the portfolio consists out of the weighted returns of the ten styles. Going short in a style i.e. negative weights are allowed. The total portfolio returns used to compare the results with the MS-VAR, the VAR and a buy-and-hold strategy.

The out-of-sample forecasts are only done with a one step and thus 1-month horizon. None of the broker models have an AR structure or any prediction power. The real-time output of first difference of the 3-month average of the broker model indicators are used to construct the 1-month ahead forecast. As a consequence, the broker models can correctly predict a transition from recovery to expansion or a transition from downturn to recession, but not from expansion to downturn or from recession to recovery. The peak-trough dating performance measure does not give any information since the broker models are by definition on month late in predicting those. Thus, in the 1-month ahead forecast only the style investment returns are used as performance measures. The Sharpe ratios of each model are constructed which can be used for comparison of performance.

The first one-third of the data is used to calculate 5 different means and 5 different variances for each of the $n = 10$ styles. The unconditional mean and variance (μ_n, σ_n^2) based and a mean and variance for each regime$(\mu_{n,s=1}...\mu_{n,s=4}, \sigma^2_{n,s=1}...\sigma^2_{n,s=4})$. At the beginning of the simulation the unconditional mean and variance are based on approximately 80 observations.

For BAML and JPM all the regime based parameters are based on around 20 observations (observations where the indicator indicated this particular regime). Since these indicators are normalized, each regime already occurred enough in the period December 1993 to Februari 2001 to do reasonable estimations for the mean and variance of every regime. For Nomura however this is not the case since the recessionary regime have very little observations. This causes for some styles to large values for the variances. For the Nomura indicator the unconditional means and variances are used for the first 5 out-of-sample observations of the recessionary regime. After this the model switches to the use of the means and variances based on the observations in the respective regimes.

The actual weights are calculated using a risk aversion parameter γ which will have a value of 5 throughout the whole research. This value is based on the paper of Kole and van Dijk [2016] but other values could be picked if an investor desires to. The weights are calculated thus:

$$w_{n,t} = \frac{\mu_{n,S_t}}{\gamma \cdot \sigma^2_{n,S_t}} \qquad S_t = 1, 2, 3, 4 \tag{1}$$

S_t is the regime corresponding value indicated by the CMI for that time step. For the buy-and-hold benchmark the weights are based on the unconditional means and variances of the styles. However out-of-sample the weights still change slightly in time since the window on which the unconditional parameters are based expands in time. The buy-and-hold portfolio is also updated and thus rebalanced every new time step, it is however still referred to as a 'buy-and-hold' strategy. Furthermore transaction costs are added for a more realistic result. The transaction costs are set at 0.15% per transaction.

As one may notice the variance of every individual style is used rather than the covariance matrix of the returns ignoring the co-movement of the styles. This gives better insight in the performance of every individual style over the indicated regimes but it implicates that optimality of the resulting portfolio is not guarantied. It does however gives clear insight in the performance of every style. The same type of weighting is naturally used for the parametric models and the benchmark strategy.

4.2 MS-VAR

As a starting point in definition and notation handling the paper of Krolzig [1997] is used. He refers to this type of MS-VAR as an MSI-VAR since the intercepts of the parameters change dependent on the regime, rather than the parameters means.

4.2.1 Model lay-out

The model I use is defined as follows:

$$Y_t = \mathcal{V}_{\mathcal{S}_t} + \Phi_{\mathcal{S}_t} Y_{t-1} + \mathcal{E}_t, \quad \mathcal{E}_t|_{\mathcal{S}_t} \sim N(0, \Sigma_{\mathcal{S}_t}) \quad , \tag{2}$$

with,

$$\Phi_{\mathcal{S}_t} = \begin{pmatrix} \phi_{y,y} & \phi_{y,r} \\ \phi_{r,y} & \phi_{r,r} \end{pmatrix}.$$

The Y-vector can be interpret as a stacked vector of all (lagged) indicator variables and the returns of the ten styles. The $\mathcal{V}$-vector are the intercepts of the variables and returns. There is a vector for each regime. The Φ-matrix is a square matrix containing the autoregressive parameters of the model. I keep the $\phi_{y,r}$ and $\phi_{r,r}$ blocks of the matrix equal to zero. Thus the regime indication is not influenced by the return series and the expected return series are solely influenced by the macro indicators and not by each other or themselves. Furthermore some logical restriction are imposed on the $\phi_{y,y}$ block, namely the influence of indicator series on leading indicators is kept zero.

As can be seen in (2) I only use lag of one month for the indicator series. I use one lag for the model because both Paap et al. [2007] and Hamilton and Perez-Quiros [1996] use this specification since it vastly reduces the number of parameters to be estimated. The MS-VAR is a VAR model subjected to switching regimes. Besides the $\mathcal{V}$-vector also the Φ-matrix and the covariance matrix depend on the regime. I allow for a different covariance matrix depending on the regime of the output variable, this is especially important since I include returns in the model. Among others, Kole and van Dijk [2016] find that regime dependent heteroskedasticity is of importance for returns. I also allow for different autoregressive parameters during each regime, since during recessions the dependence structure is likely to be different.

As is common in most of the research I define two possible different regimes, 'expansion' and 'recession'. The economy is unobservable and follows a first order Markov chain consisting out of these two regimes. The transition probabilities of this chain are defined as:

$$p_{ij} = \Pr[s_t = j|s_{t-1} = i], \text{ with } i, j \in \{0, 1\} \quad . \tag{3}$$

For the MS-VAR model I only use two regimes rather than the four I use for the brokers. With the non-parametric broker models, no elaborate estimation of parameters is needed. Therefore extra regimes do not greatly affect the model performance. The four regimes used by brokers are a result of regarding the growth and acceleration of the indicator, yielding four possible combinations each related to its own regime. In this model I choose not to include four different regimes, since extra regimes vastly increase the number of parameters to be estimated. This leads to overfitting and thus insignificant parameters and bad predictive performance. Furthermore, in other research, a third regime is added and used to capture bounce-back effects which might occur especially in the US cycle. For the EU cycle these bounce-back effects are not as likely as is shown in Artis et al. [2004]. Therefore I do not examine this option any further.

I do allow for indicator series to be implemented in the model with a lag. This implementation is rather straight forward since the data series of the indicator is just shifted a number of months. As a results both the information about the state probabilities as well as the influence of the indicator series on expected returns and other indicators is shifted.

4.2.2 Estimation

The estimation of the MS-VAR model is not much different than that of a regular univariate Markov switching model. I use the Expectation-Maximization (EM) algorithm to estimate the models parameters and the regime probabilities, a more elaborate description of this algorithm is given in Appendix B.

First a starting set of parameters is assumed, combined in $\lambda^{(0)} = (\theta, \rho, \zeta)$ wherein θ contains all parameters mentioned in (2), ρ contains the two transition probabilities p_{00}, and p_{11} and ζ is the probability of starting in regime 0 or the normal regime.

For all time steps the multivariate density of being in each regime is calculated and gathered in the vector η. Then for each time step the inference, $\hat{\xi}_{t|t}$, and then the forecast probability, $\hat{\xi}_{t+1|t}$, are calculated. The inference for the next time step incorporates the information of the density as gathered in η as well as the probability of being in a state given the state of the previous regime. The forecast probability is simply the inference times the transition probabilities and is used as input for the inference of the next time step. This calculating of inference and forecast probabilities starts at $t = 0$ and ends at $t = T$.

Then the smoothed probabilities $\hat{\xi}_{t|T}$ are calculated. These probabilities incorporate also information from the future and this algorithm works from $t = T$ to $t = 0$. Using all available information of the sample. These smoothed probabilities are used for the next step of the algorithm. The most likely set of parameters is estimated by using MLE to optimize the likelihood function defined as

$$\sum_{t=1}^{T} \log(\boldsymbol{\xi}'_{t|t-1}\boldsymbol{\eta}_t) \quad . \tag{4}$$

After this estimation the new parameter set $\lambda^{(1)}$ is used to start the estimation process again. These iterations goes on until the likelihood improvement is smaller than a certain threshold. For the standard errors of the parameters an information matrix is constructed which is asymptotically correct. The standard error can therefore become rather large when not much data is available as is the case in this research.

4.2.3 Variable selection process

As mentioned in Chapter 3 first step of the variable selection is to assess the regime switching properties of each variable individually. It is of importance that every indicator used in the model exhibits regime switching behavior for the model structure to make sense. Therefore each indicator series is tested via the LR statistic of Hansen [1992] which tests the null hypothesis of linearity against the the presence of an MSW model, $H_0 : \theta_0 = \theta_1$, with $\theta_{s_t} = (\nu_{s_t}, \sigma_{s_t}, \phi_{s_t})$ thus that the parameters in both regimes are equal. The test statistic is defined as:

$$LR_{MSW} = \mathcal{L}_{MSW} - \mathcal{L}_{AR} \quad . \tag{5}$$

The LR-statistic has a non-standard distribution which need to be determined via simulation. First I estimate AR(1) parameters based on the indicator series and use them to produce 1000 series of observations. On each set of observations a Markov switching model with one lag and an AR(1) model are estimated. Of both the log-likelihood is calculated and the difference is calculated as above. These 1000 simulated likelihood ratio tests resemble the distribution. The P-value of the likelihood ratio based on the actual data is calculated as the part of simulated LR-values larger than its own. Indicators are only used if they exhibit regime switching behaviour.

Out of the remaining variables the best coincidentally performing ones are picked and put in the MS-VAR to construct a macro-economic target variable. This target variable can be seen as the collection of all coincident macro indicators. I pick these coincident variables based on a visual assessment of the individual indicators. Especially their ability to give a clear unambiguously signal of a recession and that this signal is present around the dates given by the CEPR. These coincidental variables are then grouped together in the model explained above to indicate the macro-economic state of the Eurozone economy. This grouped variable is thus a proxy for the real latent economy. Then I continue to build up the MS-VAR by adding one leading variable at the time, both with and without switching parameters and compare the Schwarz Criterion or Bayesian information criterion (BIC). This criterion is defined as

$$-2\ln(\hat{L}) + k \cdot \ln(n),$$

wherein $\hat{L}$ represents the maximum likelihood of the model, k the number of free parameters to be estimated, and n the number of data points. First the BIC of the target variable model is calculated. Then the for each of the remaining leading variables the optimal lag is selected. In order to do so a leading variable is added for no lag, then one, etc up until 24 lags (2 years). The lag with the highest likelihood value is chosen for that variable and the variable is implemented in the model with that leading time. Then the added value of this variable is checked in a Markov switching sense by comparing the BIC of the model with switching and without switching parameters for the newly added variable. After this, the process repeats itself until the BIC of the new variable with switching parameters does not improve upon the one without switching parameters. As soon as this is the case the expanding of the model with new variables ceases and the model with optimal input is finished.

4.2.4 In-sample performance

To check in sample performance with respect to the MS-VAR model, I define a recession as the moment the probability of the recession regime is higher than 0.5 in three consecutive months. Although in literature it is more common to use six consecutive months which corresponds to the more general definition of two quarters of negative economic growth. I use three months since it corresponds with the recession definition of the brokers. It is then compared to the CEPR dates to check the performance.

The performance is also checked with respect to returns. First the parameters of the model, including the forecast probabilities are estimated based on the total data set. Then for each last two-third of the model the strategy returns are calculated. This returns are the result of a portfolio which is rebalanced after each month. It is rebalanced by calculating the optimal weights with a risk aversion parameter $\gamma = 5$. The weights are calculated for both regimes at each time step and thus both parameter sets separately:

$$w_{n,t} = \frac{\mu_{n,t}}{\gamma \sigma^2_{n,t}} \quad . \tag{6}$$

with,

$$\mu_{n,t} = \mu_{n,0,t} \cdot \xi^{s=0}_{t+1|t} + \mu_{n,1,t} \cdot \xi^{s=1}_{t+1|t} \tag{7}$$

and

$$\sigma^2_{n,t} = \xi^{s=0}_{t+1|t} \cdot (\sigma^2_{n,0,t} + \mu^2_{n,0,t}) + \xi^{s=1}_{t+1|t} \cdot (\sigma^2_{n,1,t} + \mu^2_{n,1,t}) - \mu^2_{n,t}, \tag{8}$$

where,

$\sigma^2_{n,0,t}$ is the n-th element on the diagonal of the covariance matrix of the returns $\Sigma_{0,t}$. This equations yields the weight for style n in month t conditional on the probabilities on the regimes. For the in-sample estimation $\Sigma^2_{0,t}$ and $\Sigma^2_{1,t}$ are constant over time since the whole sample is used for estimation of these matrices. Naturally the variance of individual styles is used again rather than the covariance.

This process is applied on the last two-third of the sample to obtain the cumulative style timing strategy returns, both total portfolio return as well as returns per style. Also here transaction costs of 0.15% are incorporated in the model to assess performance in a more realistic way.

Furthermore a second benchmark is added, a regular VAR model. This VAR model has the same indicator input as the MS-VAR and handles the same styles. Only difference between the VAR and the MS-VAR is the absence of two regimes in the VAR. In this way the added value of the Markov switching component can be assessed. So now there are two models taking into account macro-economic indicators to assign their style weights.

4.2.5 Out-of-sample performance

Again, to assess the 1-month-ahead forecast, I split the time series data in two parts. The first one-third is used to estimate the model parameters without future knowledge while the last two-third is used to actually do the 1-month ahead forecasts and to update the parameter values of $\mathcal{V}, \phi, \Sigma, \xi, \zeta$, and P. After this step the weights are calculated as above. So main difference with the in-sample method is that the parameters are updated each time step, rather than using the total data set to estimate the parameters. For the VAR benchmark the same method is used but only the unconditional μ's, σ's, and ϕ's are updated.

5 Results

5.1 Broker model performance

5.1.1 In-sample results

The indicators constructed by the brokers are depicted in Figure 3. The indicators are plotted against the indicated regimes and the Eurostoxx value (secondary axis). Note that the Nomura indicator has a different range in time than the other two.

It is clear to see that the indicators of BAML and JPM are normalized opposed to the Nomura indicator which handles a more official definition of a recession. Almost all the time the indicators are too late in detecting a recession or its ending. The more precise value of the error is presented in Table 4. Only the JPM indicator seems to be quite on spot with the 2011 recession. In all the other cases the indicators are 5 to 11 months overdue.

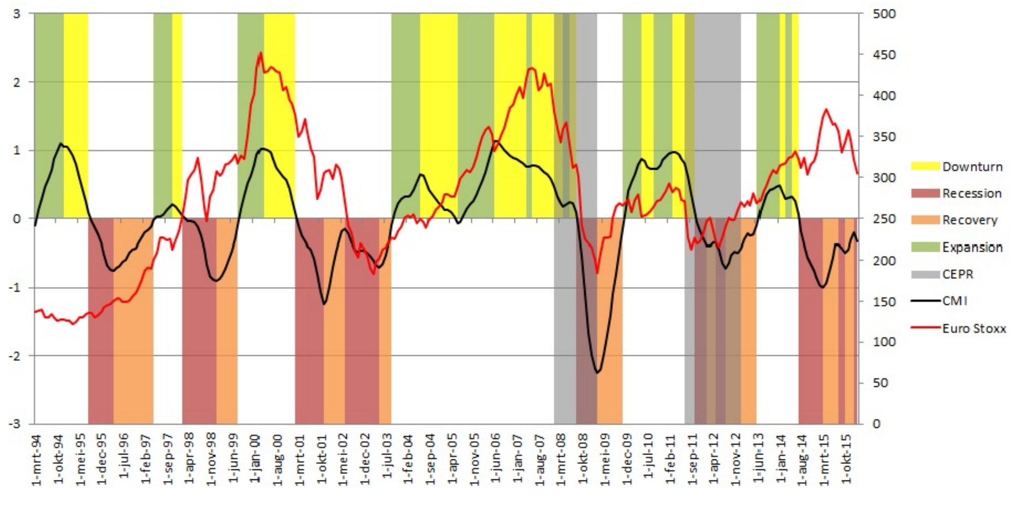
In general some potential can be seen in the leading qualities of the macro indicators for the European market, but it is (at least visually) not overwhelming. Also with respect to Table 4 the results do not give much information. With only four data points (two peaks and two troughs) it is hard to draw any hard conclusions about indication performance. Furthermore the brokers designed their indicators for the same time span as is used here. I do not know how many different indicators were tried by brokers to get these CMI's. In other words, I do not know the extend to which data-mining preceded these results.

Date	Type	BAML	JPM	Nomura
Jan '92	Peak	-	-	Jul '92 (6)
Jul '93	Trough	-	-	Apr '94 (9)
Jan '08	Peak	Sep '08 (8)	Apr '08 (3)	Sep '08 (8)
Mar '09	Trough	Nov '09 (8)	Jul '09 (4)	Dec '09 (9)
Jul '11	Peak	Nov '11 (4)	Sep '11 (2)	Jun '12 (11)
Jan '13	Trough	Jun '13 (5)	Jan '13 (0)	Aug '13 (7)

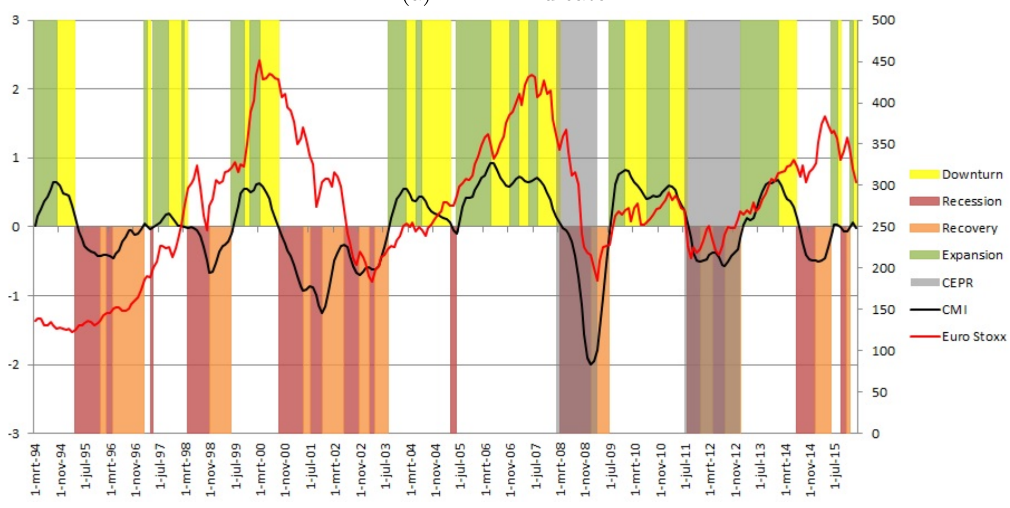
Table 4: Broker indicator performance compared to the official CEPR indicated recessions

Taking a closer look at the graphs in Figure 3 reveals that the BAML and JPM indicators follow the Eurostoxx market pretty well in the period '95-'14. They even seem to lead at some points. Outside this range however both graphs go a different direction and after 2014 they almost seem negatively correlated. The Nomura indicator leads the movement of the Eurostoxx quite well after '95, also in the more recent period. For the period before '95 it is hard to say something useful since the Eurostoxx were only introduced in '87 and the market for the stocks sort of has to grow/start-up. This is also the cause for the absent pre-'95 similarity of the other two indicators.

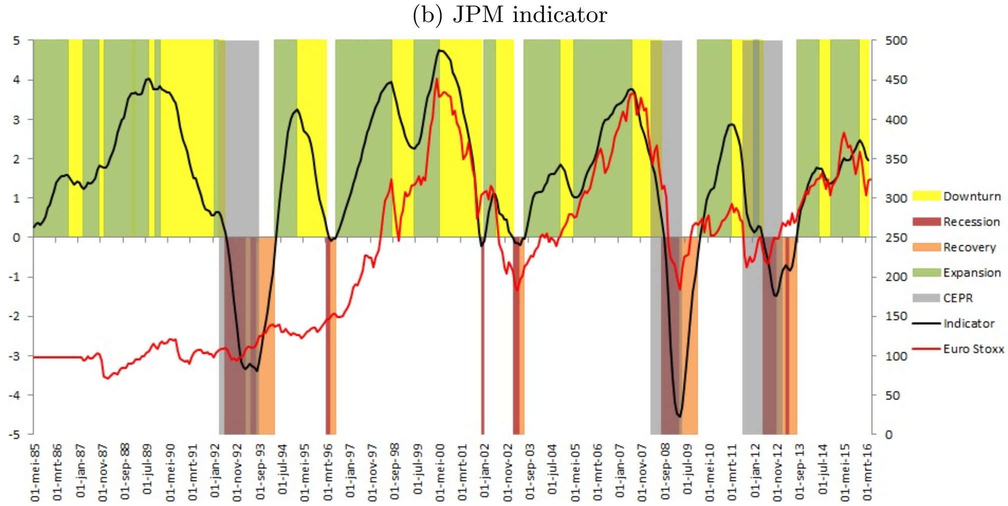
It is furthermore evident that all the CMI's show a deep trough during the 2008 crisis. A distinct difference between the macro indicator based CMI's (BAML and JPM) and the GDP based indicator of Nomura, is the second most severe crisis in the period '94-'16. The former indicate the crisis following the tech bubble as the worst while the latter indicate the '12-'13 period as such. Clearly there is a difference between the GDP growth (and thus the official CEPR dates) and signals from other macro indicators. This makes performance measurement with respect to the official CEPR dates difficult, especially when the number of false indications is considered.



(a) BAML indicator



(b) JPM indicator



(c) Nomura indicator

Figure 3: Eurostoxx, broker indicators and their indicated regimes.

5.1.2 Out-of-sample results

The results of the actual trading strategies and out-of-sample performance are shown in Figure 4 and the respective Sharpe-ratios in Table 5.

	No transaction costs			Incl. Transaction costs		
Broker	Mean(%)	Volatility(%)	Sharpe ratio	Mean(%)	Volatility(%)	Sharpe ratio
Benchmark	0.191	0.131	0.526	0.190	0.131	0.525
BAML	0.242	0.268	0.467	0.228	0.268	0.439
JPM	0.286	0.292	0.528	0.272	0.294	0.501
Nomura	0.231	0.232	0.480	0.217	0.230	0.452

Table 5: Broker strategy results (all results are per month). Realized mean, variance and Sharpe ratio

The means of the buy-and-hold benchmark of the ten styles is almost same with (0.190) and without (0.191) transaction costs. Indicating that the weight rebalancing due to the change of the unconditional means and variances is small. Without transaction costs only JPM beats the benchmark in terms of the Sharpe ratio (0.528 vs 0.526), which is caused by the increase in mean return. This difference however is clearly not significant. All the style timing strategies yield a higher volatility than the benchmark, which is a logical consequence of changing weights based on the macro-economic regimes. If the transaction costs are included the buy-and-hold benchmark has the highest Sharpe ratio (0.525). The mean return is naturally lowered by the extra costs while the volatilities of the strategies remain relatively high. In all cases however the mean return of all the broker strategies are higher.

When comparing the brokers among each other JPM has the best performance in terms of mean (0.272) and SR (0.501) and Nomura in terms of volatility (0.230). However, as mentioned before, JPM and BAML could have been subjected to data-mining while Nomura has a more intuitive straight forward approach. Also from a practical point of view, the Nomura indicator is available without any lag, while the BAML and JPM indicators can only be constructed 32 days after the end of the month. On the other hand, Nomura ignores the first 5 recession regime observations and invests based on the unconditional weights instead. This in combination with the less often signaled recession and recovery regimes probably lowered the realized volatility since the weights in those regime are relatively extreme.

Figure 4 confirms what Table 5 shows. The broker models outperform the buy-and-hold benchmark in terms of returns but do so in a more volatile way. The higher volatility can be observed in the periods where the indicators signal recessionary and recovery regimes.

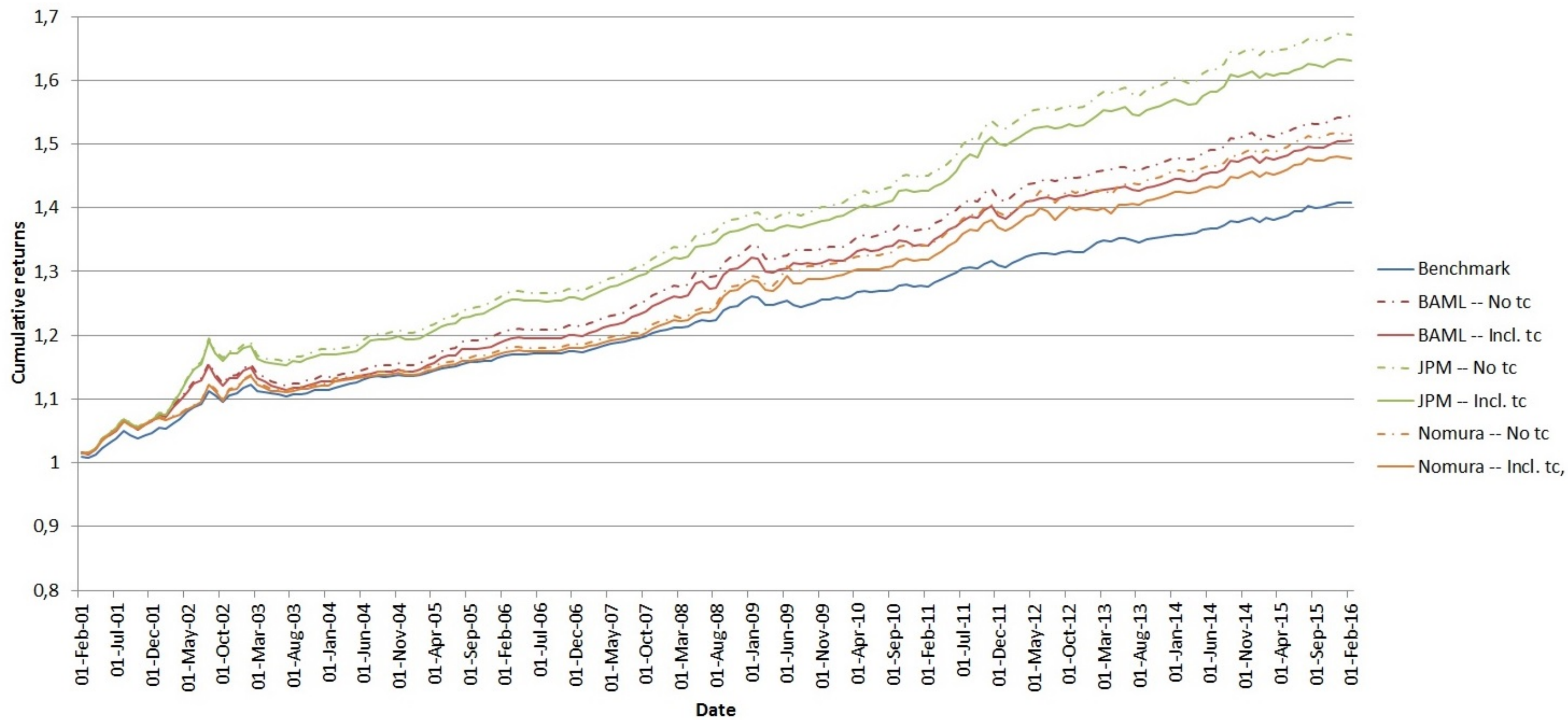


Figure 4: Broker and benchmark out-of-sample cumulative returns

Table 6 gives the results of the style timing strategy per style. These are the realized means, variances and Sharpe ratios with the weights incorporated. The corresponding graphs can be found in Appendix C. The performance of the weighted sum of the individual styles give the results of Table 5 and Figure 4.

Broker	Benchmark			BAML			JPM			Nomura		
Style	μ	σ^2	SR	μ	σ^2	SR	μ	σ^2	SR	μ	σ^2	SR
E/P	2.57	0.48	0.37	2.96	0.91	0.31	3.11	1.44	0.26	2.44	1.51	0.20
B/P	0.08	0.05	0.04	-0.16	0.25	-0.03	0.31	0.17	0.07	-0.09	0.10	-0.03
D/P	1.61	0.22	0.34	2.02	0.63	0.25	2.41	1.01	0.24	2.33	1.20	0.21
FCF	5.28	0.94	0.54	5.20	1.11	0.49	6.06	1.65	0.47	5.46	1.32	0.48
A.Rev	6.30	1.85	0.46	8.86	3.39	0.48	10.52	3.25	0.58	6.52	2.11	0.45
P.Mom	1.72	0.65	0.21	2.48	1.30	0.22	2.41	0.91	0.25	1.95	0.73	0.23
RoE	1.43	0.49	0.20	1.30	1.30	0.11	2.56	1.31	0.22	2.00	1.67	0.15
Debt/Ass	0.04	0.02	0.03	-0.14	0.25	-0.03	0.05	0.08	0.02	0.24	0.12	0.07
Beta	0.02	0.03	0.01	0.05	0.28	0.01	0.03	0.32	0.00	0.07	0.40	0.01
Size	-0.06	0.01	-0.07	0.19	0.33	0.03	-0.25	0.23	-0.05	0.77	0.27	0.15

Table 6: Total out-of-sample results per style per broker including transaction costs (mean and variance in bips (0.01%)). Note that these are realized results of the executed strategies. The investment weights of the styles are therefore incorporated in the values

This table shows that E/P, D/P, FCF, A.Rev, P.Mom, and RoE get high weights in all models. In order to check whether a style performs better with different brokers the Sharpe ratio is the best statistic. When taking the style timing into account it becomes clear that brokers improve the performance of the Analyst Revisions, Price Momentum, and Size styles in terms of the Sharpe ratio. JPM also performs better with respect to Book-to-Price and Return on Equity. While the Size style shows better results if the economic regime indicators of BAML and Nomura are used.

Earnings Yield, Dividend Yield, and Free Cash Flow have lower performance since volatility increased more than the mean returns. The beta is not largely influenced by style timing other than a high increase in volatility.

5.2 MS-VAR construction

First of all, as described in Chapter 4, each indicator is tested individually for regime switching behaviour with the Hanssen test. Then the target variable is constructed out of coincident indicators. After this the model is expanded with leading indicators until they no longer improve the model.

5.2.1 Hanssen results

The results of the Hanssen tests are given in Table 7.

	IIP	Bond Yield 12m-%	USD/SEK	M1 12m-%	EPS rev
$\mathcal{L}_{AR(1)}$	-732.15	-1784.3	-1207.5	-2115.5	-659.43
$\mathcal{L}_{MS}$	-681.92	-1707.7	-1223.7	-1976.2	-633.26
LR_{MS}	50.23	76.6	16.2	139.3	26.17
P-value	**0.002**	**0.009**	**0.016**	**0.000**	**0.000**
	CLI	ESI	Housing	Eurostoxx	M2 12m-%
$\mathcal{L}_{AR(1)}$	1088.4	-666.4	-831.4	-1015.3	-1565.0
$\mathcal{L}_{MS}$	1227.8	-635.5	-829.24	-989.773	-1480.2
LR_{MS}	139.4	30.9	2.1	25.5	84.8
P-value	**0.000**	0.052	0.924	**0.023**	**0.002**

Table 7: P-values Hanssen-test. Bold values are significant at a 5% level.

It is clear that the Economic Sentiment Indicator and the Housing permits do not exhibit regime switching behaviour significantly. The ESI indicator however is almost significant and has very good result visually if compared to the CEPR dates as can be seen in Figure 14a in Appendix A.3. That is why I decide to keep the ESI as a potential indicator for the MS-VAR. Thus, I only discard the housing indicator as a potential input series. The other eight indicators exhibit regime switching behavior significantly. They are therefore all considered potential indicators for the MS-VAR model. Switching behaviour in the month-on-month difference of the Industrial production, M1 money supply, M2 money supply, Earning per Share revisions and the Composite Leading Indicator is even significant at a 1% level.

5.2.2 Target variable

The target variable is constructed out of a pool of indicators who visually seem to match best with the CEPR recessions. These coincidental indicators are M1, EPS, ESI, and IIP and their individual graphs can be seen in Appendix A.3. The visually best result is once again obtained by combining all four series rather than a combination of three or two of the indicator series. The resulting probability of a recession as computed by the MS-VAR model with exclusively coincident indicators is depicted in Figure 5. The parameter values of this MS-VAR without any leading indicators are presented in Appendix A.4. The estimated transition probabilities, likelihood and information criterion values are also presented below the graph.

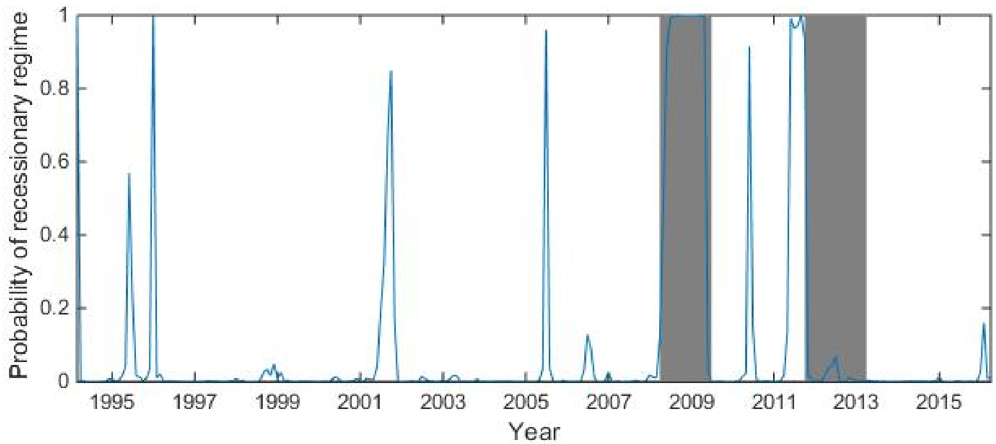


Figure 5: Regime switches as indicated by target variable consisting out of IIP, M1, ESX and ESI.

$$p_{00} = 0.967, \quad p_{11} = 0.687, \quad \hat{L} = -2469.0, \quad \text{BIC} = 5237.5 \quad .$$

As can be seen from the graph the fit is not very good in general with exemption of the 2008 crisis, which is not surprising as it is such a severe one. This combination of coincidental indicators, however, gives the least 'false' identifications of recessionary regimes. It does adequately indicate the beginning of the 2011 crisis some months ahead, but fails to indicate the rest of this recession as such. Further interpretation of this graph is given after the model is expanded with leading indicators in the next section.

5.2.3 Final model specifications

Next, to improve the model, leading indicators are added to the VAR structure to see if the model improves. A random potential leading indicator is added to the MS-VAR. First with no lags, then 1 lag and so on up to 24 lags. Lag with the best improvement to maximum likelihood value is selected. The variable is added with and without switching to check if adding this indicator actually improves the model. To do so, both the BIC values of the model with the switching leading indicator and the non-switching leading indicator are compared. If the BIC value of the model with the regime switching leading indicator is lower than the BIC value of model with the non-regime switching indicator, the indicator is added with its optimal lag. Otherwise the indicator is not included in the model. Table 8 shows the results.

Indicator	Optimal lag	BIC switching	BIC non-switching
CLI	5	4407.9	4562.9
EPS Revisions	2	5584.6	5597.8
Bond Yield 12m-%	9	7837.5	7783.0
USD/SEK	11	9427.1	9371.5
M2 12m-%	2	10201.2	10133.5

Table 8: Optimal lags of different indicators

The EPS revisions and M2 money supply might be seen as an coincident indicators since the lag is rather small compared to the target variable. There are furthermore only two indicators which add information to the model in a regime switching sense. These two, the CLI with a lag of 5 months and the Earnings per Share revisions with a lag of 2 months. These two are therefore added to the model while discarding the rest. The final model which indicated the economic regime thus consists out of four coincident indicators and two leading indicators.

Below, in Tables 9 to 14, part of the parameters of the final model are given, based on the entire sample from 1993 until now. Using the definitions of equation (2) in Methodology only the non-zero elements of the model are presented i.e. $\mathcal{V}_{\mathcal{S}}$ (Table 9), $\phi_{\mathcal{S},y,y}$ (Tables 10,11) and $\phi_{\mathcal{S},r,y}$ (Tables 12,13). Also the parameters of a regular VAR model without regime switching are given for comparison (Tables 9,14). The bold values are significant at a 5% level.

The first general observation that catches the eye is that none of the recessionary regime parameters are significantly different from zero. This is due to the fact that the standard errors of the parameters are very high, which is a consequence of the small number of observations with a large probability for this regime. The construction method of the standard errors is asymptotically correct, but due to the lack of observations these errors are rather large, yielding all parameters insignificant. The standard errors are exorbitantly high so I question whether these errors can be considered reliable. Since overfitting is a distinct possibility, this needs to be considered.

The MS-VAR model indicates only 27 observations with a probability larger than 50% and not many more with a probability between 10% and 50%. Since the second regime has 31 parameters that need to be estimated for the macro indicator autoregressive part it is likely that the model is close to or slightly overfitted. This makes the interpretation of the recessionary regime parameter values and their standard errors in the coming tables impossible to interpret in a correct way. The overfitting is even worse with the influence of the macro indicators on the style returns. Seventy parameters are to be estimated for the recession regime while only the same low number of recession observations are signalled. Overfitting is certain for this part of the matrix yielding the results of Table 13 and the second part of the middle column of Table 9 incorrect. I will treat the numbers but with a more qualitative view rather than a quantitative one.

Table 9 gives the intercepts of the macro indicators and all the styles for both economic regimes and a regular VAR-model. The VAR model has the same significant parameters as the non-recession regime of the MS-VAR. This is also expected since the non-recession regime is signalled most of the time. Values of the significant VAR intercept are also very close in value to that of the 0-regime of the MS-VAR. When taking a look at the macro indicator the parameter value of the VAR model is in between that of the values of the MS-VAR regimes but always closer to that of the non-recession regime with the exemption of the ESI indicator. The VAR parameters look like to be a sort of weighted average of both regimes as is to be expected. This 'weighted average' result however is only present in the macro indicators on which the regimes are based. In the style intercepts the VAR intercept is mainly outside of both MS-VAR values. Although still always very close the the non-recession regime value, this is caused by the overfitting in the recessionary regime. Otherwise one would expect the VAR values to be in between both regimes. I do however continue with this model since it was the initial set-up for the study. The regular VAR model performance w.r.t. the brokers and thus a parametric model v.s. non-parametric models can still be compared.

	$\mathcal{V}_0$		$\mathcal{V}_1$		$\mathcal{V}_{VAR}$	
Indicator/Style	Intercept	(std err)	Intercept	(std err)	Intercept	(std err)
IIP	**0.211**	(0.079)	0.137	(28.6)	**0.182**	(0.052)
M1	-0.863	(0.823)	17.721	(1509.5)	0.662	(0.903)
ESX	0.503	(0.505)	-1.157	(155.9)	0.381	(0.278)
ESI	-0.042	(0.128)	-0.169	(59.0)	0.066	(0.089)
CLI(5)	-0.001	(0.003)	0.027	(6.6)	0.000	(0.002)
EPS(2)	-0.218	(0.259)	0.398	(563.9)	-0.205	(0.159)
E/P	**0.950**	(0.273)	0.631	(64.5)	**0.894**	(0.291)
B/P	0.142	(0.305)	-1.088	(161.4)	0.181	(0.382)
D/P	**0.686**	(0.288)	1.386	(43.2)	**0.690**	(0.305)
FCF	**0.803**	(0.158)	1.105	(50.1)	**0.786**	(0.190)
A.Rev	**0.969**	(0.202)	1.188	(84.0)	**0.918**	(0.223)
P.Mom	**1.389**	(0.474)	1.182	(237.7)	**1.105**	(0.512)
RoE	**0.563**	(0.223)	0.918	(66.8)	**0.552**	(0.254)
Debt/Ass	0.056	(0.166)	0.560	(72.6)	0.098	(0.179)
Beta	0.496	(0.734)	1.877	(297.1)	0.293	(0.730)
Size	-0.020	(0.310)	-0.536	(121.2)	0.019	(0.319)

Table 9: Intercept values of MS-VAR (regime 0 and 1) and VAR model. Their standard errors are within the brackets. Bold values are significant at a 5% level.

In the macro indicator part (first six values) of the $\mathcal{V}_\mathcal{S}$ vectors only the IIP intercept in the non-recession regime is significantly different from zero. This suggests that the month on month growth in the industrial production after correction for the influence of the other indicators is on average positive. Also the intercepts of six style returns are still significantly higher than zero at a 5% level. These styles seem to do better in a calm economy. When looking at the intercepts of the recession regime some styles swing quite a lot in the intercept. Book-to-Price and Size perform way worse in difficult periods, while all other styles perform better after correction of macro indicator influence. Though keep in mind that the parameters in this regime are probably subjected to overfitting.

Below is the part of the Φ-matrix which is used to determine the regimes of the MS-VAR model, the autoregressive parameters of the macro indicators. This part of the model is therefore not compared to the VAR model.

Indicator	IIP	M1	ESX	ESI	CLI(5)	EPS(2)
IIP	**-0.455**	-0.004	0.004	0.108	0.718	0.021
	(0.086)	(0.006)	(0.019)	(0.064)	(0.736)	(0.016)
M1	1.232	**0.451**	0.181	-0.527	-7.301	-0.179
	(1.080)	(0.074)	(0.209)	(0.814)	(8.093)	(0.190)
ESX	-0.543	0.036	**0.255**	0.161	0.862	0.001
	(0.535)	(0.041)	(0.092)	(0.403)	(4.425)	(0.108)
ESI	0.208	0.008	0.046	**0.249**	**3.036**	-0.025
	(0.141)	(0.016)	(0.030)	(0.105)	(1.028)	(0.026)
CLI(5)					**0.899**	
					(0.026)	
EPS(2)					-2.035	**0.887**
					(2.275)	(0.052)

Table 10: Autoregressive parameter values of the macro indicators of the non-recessionary regime (0) of the MS-VAR model. Their standard errors are within the brackets. Bold values are significant at a 5% level.

Indicator	IIP	M1	ESX	ESI	CLI(5)	EPS(2)
IIP	-0.055	-0.011	0.058	0.183	-1.781	0.074
	(22.4)	(1.6)	(4.5)	(13.1)	(154.2)	(5.1)
M1	-2.924	0.436	2.797	-6.243	-54.110	1.937
	(1410.9)	(27.7)	(155.8)	(422.8)	(9068.4)	(268.3)
ESX	-2.384	-0.092	-0.143	1.127	-15.618	0.338
	(191.1)	(8.8)	(36.2)	(122.4)	(901.3)	(39.4)
ESI	0.057	-0.027	0.003	0.748	-2.475	-0.011
	(73.6)	(2.9)	(14.1)	(36.4)	(325.3)	(16.2)
CLI(5)					0.832	
					(43.8)	
EPS(2)					4.281	0.631
					(2443.1)	(93.9)

Table 11: Autoregressive parameter values of the macro indicators of recessionary regime (1) of the MS-VAR model. Their standard errors are within the brackets. Bold values are significant at a 5% level.

$$p_{00} = 0.968, \quad p_{11} = 0.703, \quad \hat{L} = -2543.7, \quad \text{BIC} = 5584.6 \quad .$$

The diagonal elements of $\phi_{0,y,y}$ in Table 10 are clearly significant, contrary to most of the non-diagonal elements. The diagonal of $\phi_{1,y,y}$ in Table 11 are again not significant due to the errors but no extreme values are present (close to overfitting). The autoregressive influence of the IIP decimates to almost none in the recession regime, while the influence of the Economic Sentiment on itself almost triples in recession. The one sign change in the autoregressive diagonal is that of the EuroStoxx of which the dependency seems to turn during a recession.

The only non-diagonal significant parameter is the influence of the Composite Leading Indicator of five months ago on the Economic Sentiment Indicator. This could suggest that the CLI is quite capable in assessing the economic sentiment five months ahead. Also this parameter switches sign in the recession regime.

The transition probabilities show that due to the adding of the two leading indicators the chance to remain in a recession is slightly higher than without these two. The chance to stay in the calm economic state is unaltered.

More interesting for this research however is the influence of the macro indicators on the different styles as shown below in Tables 12 and 13. Again the Φ-parameters of a normal VAR-model are shown for comparison purposes in Table 14. The bold values are significant at a 5% level and the values marked with a $(*)$ are significant in the VAR-model but not in the MS-VAR model.

Again for all the parameters significant in the VAR-model, the VAR parameters are in between the values of both MS-VAR regimes. They are, however, not always closer to the 0-regime value. When comparing these coefficients it is noticeable that none but the M1-A.Rev parameter change sign. In an absolute sense the values in the recession regime are larger resulting in a high influence of the macro indicators on the styles during difficult times. The market reacts more to the indicators during harsh economic times. It also indicates a more volatile market for the styles which is to be expected. Although clear interpretation of the recession parameters remains impossible due to overfitting in this regime.

Indicator	IIP	M1	ESX	ESI	CLI(5)	EPS(2)
E/P	0.219	0.009	-0.035	-0.134	-0.664	0.006
	(0.371)	(0.039)	(0.067)	(0.184)	(2.430)	(0.059)
B/P	0.045	0.025	-0.055	0.090*	-0.396*	0.012
	(0.385)	(0.035)	(0.080)	(0.222)	(2.895)	(0.073)
D/P	0.225	0.004	-0.102*	-0.147	-0.182	-0.028
	(0.389)	(0.038)	(0.063)	(0.210)	(2.463)	(0.063)
FCF	0.207	0.016*	-0.031	-0.131	1.088	-0.011
	(0.200)	(0.019)	(0.040)	(0.110)	(1.536)	(0.044)
A.Rev	-0.189	-0.009*	0.068*	0.073	0.165*	0.022
	(0.209)	(0.018)	(0.045)	(0.136)	(1.479)	(0.039)
P.Mom	0.012	-0.019	0.046	-0.061	-1.256	-0.015
	(0.486)	(0.041)	(0.102)	(0.314)	(3.448)	(0.097)
RoE	0.024	-0.005	0.010	-0.176*	0.654	-0.003
	(0.301)	(0.025)	(0.065)	(0.161)	(1.772)	(0.047)
Debt/Ass	-0.047	-0.014	0.007	-0.064*	0.690	0.004
	(0.188)	(0.016)	(0.035)	(0.123)	(1.326)	(0.031)
Beta	0.025	-0.024	0.061*	-0.357*	-1.647	0.029
	(0.843)	(0.092)	(0.140)	(0.470)	(5.564)	(0.149)
Size	-0.131	-0.007	**0.178***	0.068	-1.153	0.011
	(0.353)	(0.034)	(0.052)	(0.193)	(2.726)	(0.063)

Table 12: Parameter values of the macro indicator influence on the styles in the non-recessionary regime (0) of the MS-VAR model. Their standard errors are within the brackets. Bold values are significant at a 5% level. Values marked with a (*) are significant in the regular VAR model but not in the MS-VAR.

Indicator	IIP	M1	ESX	ESI	CLI(5)	EPS(2)
E/P	0.498	0.002	-0.002	0.058	2.263	-0.156
	(65.9)	(2.1)	(8.4)	(32.4)	(341.4)	(16.9)
B/P	-0.040	-0.038	-0.197	0.656*	-7.230*	-0.021
	(164.6)	(10.1)	(30.5)	(103.5)	(1449.7)	(46.6)
D/P	0.274	-0.003	-0.040*	-0.041	3.355	-0.110
	(56.8)	(1.4)	(9.3)	(24.4)	(530.4)	(12.6)
FCF	-0.309	0.012*	0.030	-0.009	-3.063	0.112
	(41.8)	(1.0)	(8.8)	(21.0)	(446.4)	(9.2)
A.Rev	0.483	0.037*	0.144*	-0.221	5.971*	-0.114
	(83.7)	(4.7)	(11.1)	(33.7)	(715.6)	(20.2)
P.Mom	-0.239	0.042	0.332	-0.775	7.109	0.112
	(215.2)	(13.3)	(31.4)	(98.5)	(2054.0)	(57.8)
RoE	0.424	0.009	0.080	-0.262*	4.393	-0.109
	(76.9)	(5.0)	(12.6)	(41.2)	(413.6)	(14.3)
Debt/Ass	0.053	0.018	0.073	-0.301*	0.848	0.000
	(65.5)	(4.7)	(9.1)	(33.0)	(612.1)	(14.8)
Beta	1.158	0.051	0.345*	-0.922*	16.716	-0.179
	(296.8)	(12.9)	(51.1)	(142.0)	(2931.0)	(79.2)
Size	0.085	-0.011	0.045*	0.237	3.584	-0.156
	(114.1)	(5.4)	(12.2)	(36.9)	(489.8)	(14.9)

Table 13: Parameter values of the macro indicator influence on the styles in the recessionary regime (1) of the MS-VAR model. Their standard errors are within the brackets. Bold values are significant at a 5% level. Values marked with a (*) are significant in the regular VAR model but not in the MS-VAR.

Indicator	IIP	M1	ESX	ESI	CLI(5)	EPS(2)
E/P	0.212	-0.003	-0.016	-0.070	-1.030	-0.012
	(0.164)	(0.009)	(0.033)	(0.093)	(1.152)	(0.030)
B/P	0.055	-0.015	-0.063	**0.293**	**-3.428**	-0.014
	(0.216)	(0.012)	(0.043)	(0.122)	(1.516)	(0.039)
D/P	0.209	-0.003	**-0.083**	-0.101	-0.023	-0.032
	(0.172)	(0.009)	(0.035)	(0.097)	(1.210)	(0.031)
FCF	0.185	**0.013**	-0.014	-0.047	0.313	0.001
	(0.107)	(0.006)	(0.022)	(0.060)	(0.752)	(0.019)
A.Rev	-0.158	**0.014**	**0.074**	-0.038	**1.561**	0.020
	(0.126)	(0.007)	(0.025)	(0.071)	(0.885)	(0.023)
P.Mom	0.048	0.009	0.100	-0.298	3.141	0.039
	(0.289)	(0.016)	(0.058)	(0.163)	(2.030)	(0.052)
RoE	.040	0.001	0.023	**-0.195**	1.081	-0.008
	(0.143)	(0.008)	(0.029)	(0.081)	(1.006)	(0.026)
Debt/Ass	-0.079	0.007	0.005	**-0.127**	0.995	0.001
	(0.101)	(0.006)	(0.020)	(0.057)	(0.711)	(0.018)
Beta	0.164	0.009	**0.117**	**-0.551**	2.990	0.067
	(0.413)	(0.022)	(0.083)	(0.233)	(2.896)	(0.075)
Size	-0.182	-0.008	**0.154**	0.045	-0.650	-0.010
	(0.180)	(0.010)	(0.036)	(0.102)	(1.264)	(0.033)

Table 14: Parameter values of the macro indicator influence on the styles in the VAR model. Their standard errors are within the brackets. Bold values are significant at a 5% level.

In the $\phi_{\mathcal{S},r,y}$ part of the Φ matrix only one parameter is significant again due to data limitations making interpretation somewhat difficult. The influence of the monthly change in Eurostoxx on the Size style, 0.178, suggests that a growth in Eurostoxx in the previous month has a positive influence on the return of the Size portfolio.

For the influence of some macro-economic indicators on investment styles it is clear that dividing the economy in two different regimes has more use than for others. The influence of the Composite Leading Indicator shows large differences between the two regimes as well as EPS and IIP for certain styles. Although clear interpretation of the parameters remains difficult due to the lack of significant ones. Of all the indicators the IIP and the Earnings per Share revisions have no significant influence on any of the styles. The monthly change in the Eurostoxx price index and the European sentiment indicator seem to influence most styles.

From the perspective of the styles Earnings Yield and Price Momentum are not significantly influenced by any of the considered macro indicators. Book-to-Price, Beta, and Analyst Revisions on the other hand are influenced by two or more indicators. For Analyst Revisions this is less surprising as analysts need to base their analysis on some external indicators themselves. The Composite Leading Indicator of five months ago has a positive relation with the returns of the Analyst Revisions but a strong negative connection to the Book-to-Price style.

So for the expected returns of the styles for the following month the M1, ESX, ESI, and CLI indicators are important, while IIP and EPS are important for detecting and predicting regimes. Price Momentum and Earnings Yield are hard to predict using the currently selected indicators. Price Momentum probably benefits more from autoregressive elements, which are omitted for the style part of this model. Also the marcro-economic influence on the Earnings-to-Price ratio is small. Apparently these indicators influence the companies earnings roughly the same way as the price is influenced, keeping the change in E/P small and the parameters not significantly different from zero.

In general the MS-VAR model is working as it should an the estimated parameters and transition probabilities have reasonable values. The model adequately splits the economy in a steady calm regime of with the parameter values are close to that of a regular VAR-model and in a regime which has more extreme values. This recessionary regime has more extreme parameter values for the intercepts, autoregressive macro indicator influence and macro indicator influence on the styles. If I would construct the model again Earnings yield and Price momentum would be omitted as potential investment styles.

This being said also some less positive remarks can be made. The fact that the parameters in the VAR model are significant does indicate that it can be useful to include macro indicators in style timing. The Markov Switching however contributes little to nothing with the current series length and data availability.

5.3 MS-VAR performance

Figure 6 gives the smoothed recessionary regime probability in the period 1994 to 2016 as indicated by the model of which the parameters are described at the end of Section 5.2.

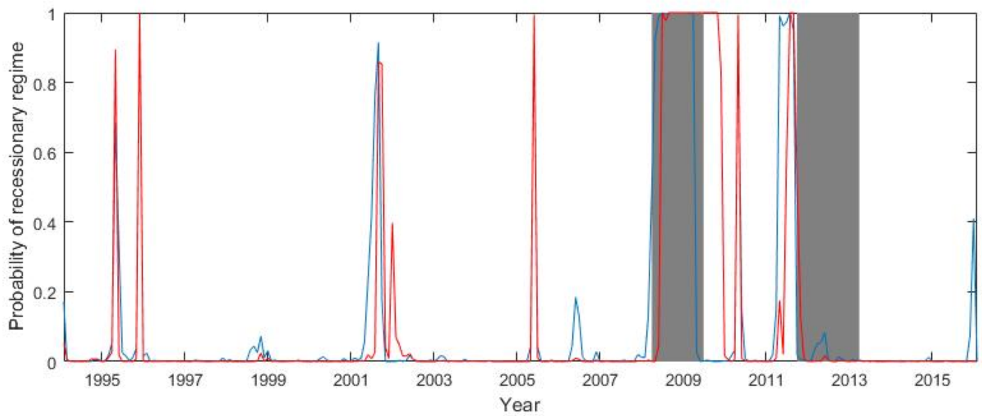


Figure 6: Regime probabilities indicated by MS-VAR model with (r) and without (b) leading indicators

In the graph above the effect of the two added leading indicators on the recession probability is shown. In the red line the CLI(5) and EPS(2) are included. In general it is a nice result with a good balance between recession and non-recession periods. Most of the time the calm economic regime is signalled as is the case in the real economy. The tech bubble and 2009 crisis are clearly present as well, indicating that the model works and the input data represents the economy quite well despite lingering overfitting problems. Three 'false' recessions are signaled while the last 'official' recession is signalled too early. Although 'false' is probably the wrong term as the CEPR indications are also based on models and rules.

Comparing this graph to the broker models in Figure 3 sheds some more light on the results. This 2011 crisis is also less pronounced in the regime indication by the macro indicators based broker models of BAML and JPM. These indicators show deeper troughs for the tech bubble and November 2014 than 2011. The GDP-based Nomura indicator on the other hand shows the deepest trough during the 2011 crisis, compared to November 2014 and the tech bubble. This suggests that the 2011-2012 crisis was mainly a dropping GDP growth and less observable in other indicator data. This could be an explanation for the bad MS-VAR fit on the official GDP-based CEPR dates and the 'false' indications of '95 and '01.

After adding of the leading indicators the fit does not change much compared to the coincidental indicator based model (blue graph). The recession probability in early 2002 is more pronounced compared to the model consisting solely out of coincident indicators, although it is signalled somewhat later. Second difference is the slightly better indication of the 2012 recession, which starts closer to the actual crisis date. Thirdly the 2009 recession has a worse fit, starting later and lasting longer.

In Table 15 the CEPR dates are compared with the MS-VAR model, which gives a more precise interpretation than the graph above. As mentioned earlier a recession is defined as three consecutive months wherein the probability of a recession is more than 0.5. The MS-VAR model also performs worse than all broker models. With exemption of the start of the 2011 crisis, the model is always off by at least 2 quarters, which is quite a lot.

Date	Type	MS-VAR
-	Peak	Jan ’02 (-)
-	Trough	Jul ’02 (-)
Jan ’08	Peak	Nov ’08 (10)
Mar ’09	Trough	Nov ’09 (8)
Jul ’11	Peak	Jul ’11 (0)
Jan ’13	Trough	Nov ’11 (-14)

Table 15: MS-VAR recession indication performance compared to CBER dates

5.3.1 In-sample v.s. Out-of-Sample performance

Table 16 shows the performance of the VAR and MS-VAR based strategies. In-sample, the parameters of the model are estimated using all data up to 2016. Out-of-sample the estimation of the parameters only uses information up to t and the parameter set is updated each time step. It becomes clear that in-sample the MS-VAR performs better than the VAR benchmark in terms of the Sharpe ratios. The better performance of the MS-VAR in-sample compared to the VAR in-sample is due to a higher mean which improves enough in order to enlarge the Sharpe ratio despite a higher realized volatility.

In order to check whether the Sharpe ratio of the MS-VAR in-sample is significantly larger than the VAR strategy a test is performed. The used test is developed by Ledoit and Wolf [2008] and tests if a Sharpe ratio of a strategy is significantly different. It is robust against heavier tails in return distribution and time series characteristics. It is also applicable to smaller samples like mine. These advantages are realized by the use of studentized time series block bootstrap. The optimal block size found for these strategy returns is 6. The test statistic yields 0.790 with a p-value of 0.449. The difference of the Sharpe ratios of the strategies is thus not significantly larger than 0.

When looking at the out-of-sample strategy the VAR and MS-VAR perform almost identical and the effects of the Markov Switching parameters disappears entirely.

Model	Incl. Transaction costs		
	Mean(%)	Volatility(%)	Sharpe ratio
VAR Benchmark i.s.	0.239	0.125	0.647
MS-VAR i.s.	0.259	0.153	0.677
VAR Benchmark o.o.s.	0.222	0.186	0.515
MS-VAR o.o.s.	0.224	0.188	0.515

Table 16: MS-VAR in-sample v.s. out-of-sample strategy results (all results are per month)

The graph in Figure 7 shows that the main difference between the in-sample and out-of-sample performance for both models occurs during the big crisis in 2009. The out-of-sample strategies experience a slight dip before they adjust the weights and they start making profit again. In-sample this dip is countered by more certain regime indication and a better estimated parameters for the recessionary regime. Another difference between in-sample and out-of-sample is the number of recessions prior to 2009 which is higher in case of the out-of-sample results. This is explained by the effect that the 2009 crisis was so severe, also in the macro-economic variables, that after this crisis the criteria for indicating a recession as such were became more strict. This is backed by the fact that the probability of a recession within the forecast probabilities itself changes after 2009 which indicates clearly less recessions. The more frequent regime switches have however little influence on the performance. The MS-VAR and VAR in-sample. perform roughly the same as the MS-VAR and VAR do out-of-sample up to 2009. If one would like to get a better notion of less severe recessions after the 2009 crisis it might be interesting to add a third regime coping with crash recession types such as the 2009 crisis. Since adding a third regime brings even more parameters and given the significance problems I already encounter I will not pursue this option further. The extra regime also makes more sense when the

MS-VAR is applied directly to stock market data rather than to the macro-economic cycle.

After the 2009 crisis the out-of-sample MS-VAR underperformes for a while but catches up with the VAR model in the 2011 recession. This might suggest that for the last recession the macro indicator parameters are better estimated due to the extra data of the large crisis in 2009. However this improved MS-VAR performance is also clearly visible in-sample where model parameter values do not change in time. The picked set of macro variables apparently benefit from the Markov Switching parameters during this last short crisis. Whether this result remains in the future is impossible to say, but it is a remarkable observation.

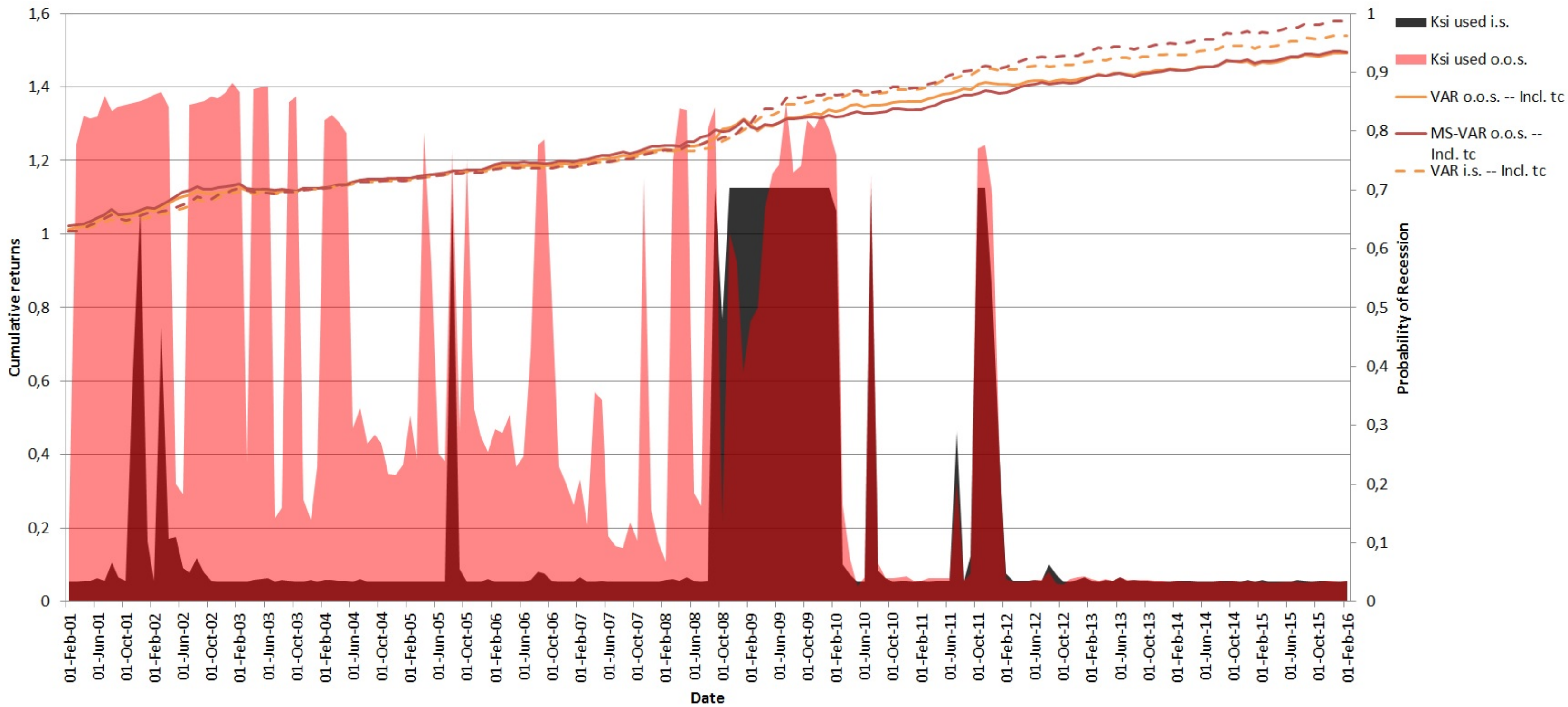


Figure 7: MS-VAR and VAR in-sample and out-of-sample cumulative returns including transaction costs. Below are the forecast probabilities used to determine the weights of the MS-VAR model

5.4 Comparison to benchmark broker models

The ultimate results of this report are presented in this section. I only compare the MS-VAR and VAR to the best performing broker, JPM, in order to keep it orderly. Table 17 gives the mean, volatility and Sharpe ratios of the four considered strategies: Buy-and-hold-benchmark, the VAR investment based benchmark, the MS-VAR and the JPM rule based strategy. All are including transaction costs and out-of-sample strategies. All four take a first position on February 2001 and the last incorporated returns are from February 2016.

Model	Incl. Transaction costs		
	Mean(%)	Volatility(%)	Sharpe ratio
Benchmark	0.190	0.131	0.525
JPM	0.272	0.294	0.501
VAR	0.222	0.186	0.515
MS-VAR	0.224	0.188	0.515

Table 17: MS-VAR, VAR and broker strategy results (all results are per month)

The JPM CMI based strategy has the highest mean returns per month (0.27%) while the VAR models have 0.22% and the the benchmark only 0.19% per month. Better Sharpe results are therefore only induced by the lower volatility of the strategies. These volatility differences are expected by model construction. The JPM strategy has four different sets of weights which incites large jumps in investment weights, which in turn drive the volatility of the strategy. MS-VAR and VAR alter weights on macro input which yields to less rigorous jumps in the weighing scheme, but it still incites more volatility in of the strategy than a simple buy-and-hold. So when the Sharpe ratios are compared it is clear that the buy-and-hold benchmark performs best (0.525) followed by the VAR and MS-VAR (0.515) and finally the J.P. Morgan macro indicator (0.501). The exact opposite compared to the means and thus solely induced by the volatility of the strategies. Again non of the strategies perform significantly better than others according to the test of Ledoit and Wolf [2008]. Although one must keep in mind that the strategies are not optimal. So slightly better relative performance of the J.P.Morgan and VAR models can be expected if the co-movement of the styles is taken into account in the weighting schemes.

When looking at the graph in Figure 8 the performance of the different strategies in time is shown. Below the probability of a recession is plotted. The black graph shows the smoothed probabilities as constructed at the end of the sample (different than in Figure 6). The red, transparent probabilities are the forecast probabilities, $\hat{\xi}_{t+1|t}$, estimated using only information up to that point in time and used for determining the MS-VAR investment weights.

As can be seen in Figure 8 the difference in cumulative returns is clear. Both the VAR and the MS-VAR are around 150% in a cumulative sense in those 15 years. While the JP Morgan based strategy reaches over 160% and the buy-and-hold benchmark ends up around 140%. 10% difference in 15 years of investment is not necessarily much. It certainly does not indicate that one strategy is clearly better than the others. All strategies exhibit little volatility due to the risk aversion parameter of 5 although difference between the strategies remain observable. Especially the volatile start of the JPM indicator compared to the other strategies. This volatile movement is caused by a series of recession and recovery regimes during 2001-2003. The second jump of the JPM strategy compared to the buy-and-hold is during the last crisis of 2011. As stated before also the MS-VAR performes also better during this crisis. This better performance might simply be the effect of data-mining. This crisis falls within the period which JPM used to pick their macro indicators. I do not know how many indicators JPM tried in order to construct their CMI, but it is likely they used the ones that did well during this last crisis. Since the indicators used by JPM were also my starting point in looking for indicators for the (MS-)VAR this effect could also influence the MS-VAR performance. As a result also the after-crisis performance of the MS-VAR and VAR could be enhanced due to data mining by JPM. It is therefore possible that future out-of-sample model performance is worse compared to the 2010-2015 period for both the VAR as well as the JPM and BAML broker models.

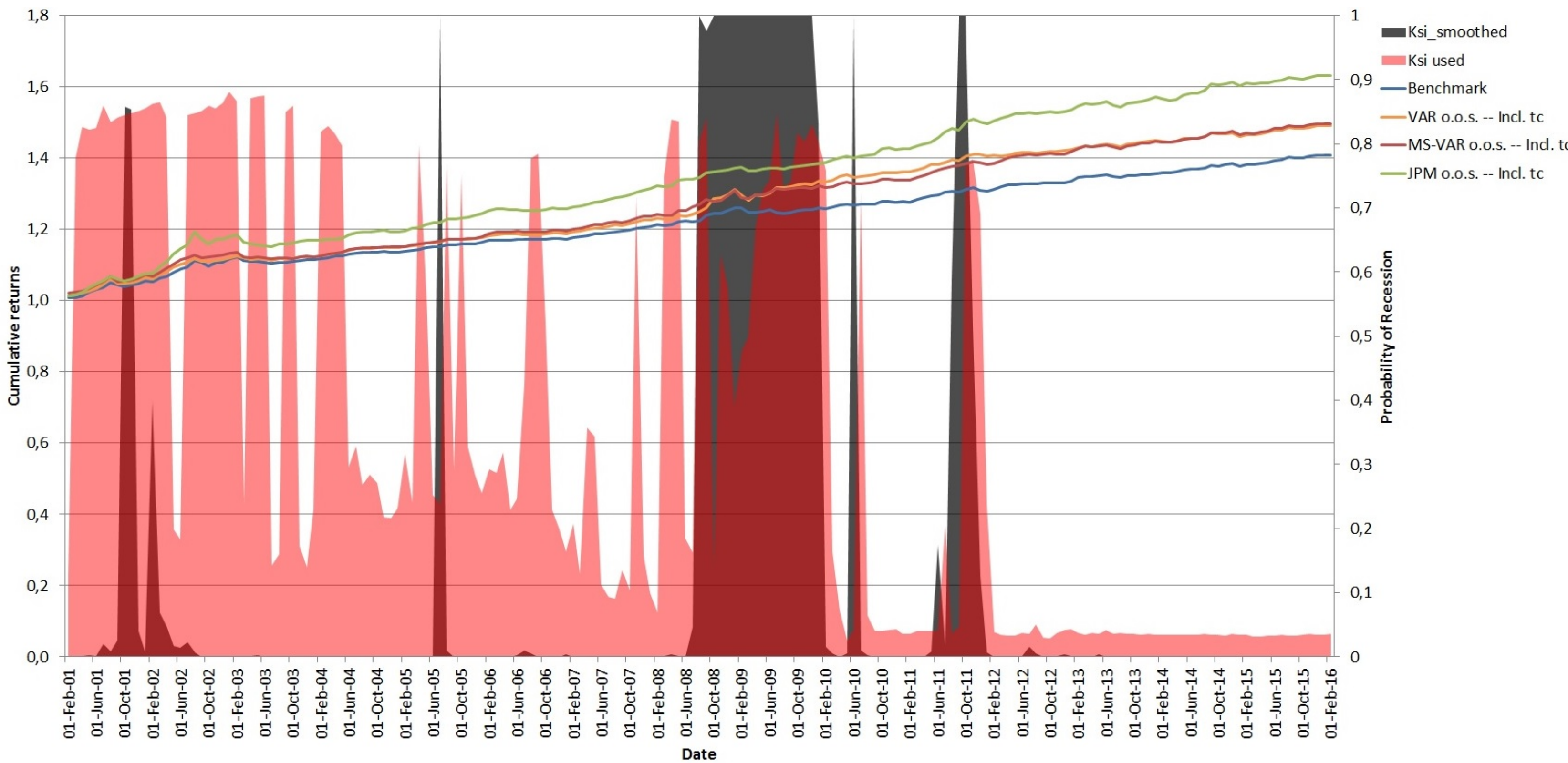


Figure 8: Broker, MS-VAR and benchmark out-of-sample cumulative returns including transaction costs

The performances per style are presented in Table 18. These are the realized means, variances and Sharpe ratios with the weights incorporated. The corresponding graphs can be found in Appendix C.

Broker	Benchmark			JPM			VAR			MS-VAR		
Style	μ	σ^2	SR	μ	σ^2	SR	μ	σ^2	SR	μ	σ^2	SR
E/P	2.57	0.48	0.37	3.11	1.44	0.26	2.45	0.78	0.28	2.42	1.03	0.24
B/P	0.08	0.05	0.04	0.31	0.17	0.07	0.86	0.76	0.10	0.88	0.55	0.12
D/P	1.61	0.22	0.34	2.41	1.01	0.24	2.36	0.79	0.27	2.37	0.92	0.25
FCF	5.28	0.94	0.54	6.06	1.65	0.47	4.47	1.65	0.35	4.26	1.31	0.37
A.Rev	6.30	1.85	0.46	10.52	3.25	0.58	7.06	1.64	0.55	7.97	1.95	0.57
P.Mom	1.72	0.65	0.21	2.41	0.91	0.25	2.14	1.11	0.20	2.75	1.24	0.25
RoE	1.43	0.49	0.20	2.56	1.31	0.22	1.85	0.50	0.26	1.37	0.52	0.19
Debt/Ass	0.04	0.02	0.03	0.05	0.08	0.02	0.76	0.58	0.10	0.12	0.54	0.02
Beta	0.02	0.03	0.01	0.03	0.32	0	0.21	0.23	0.04	0.43	0.31	0.08
Size	-0.06	0.01	-0.07	-0.25	0.23	-0.05	0.07	0.36	0.01	-0.22	0.34	-0.04

Table 18: Total out-of-sample realized results per style per strategy including transaction costs (mean and variance in bips (0.01%)). Note that these are realized results of the executed strategies. The investment weights of the styles are therefore incorporated in the values.

First comparing the Sharpe ratios of the VAR versus those of the MS-VAR, only the Price Momentum and Beta style show a prominent improvement in performance (0.20 to 0.25 and 0.04 to 0.08 respectively) when model parameters are subjected to Markov Switching. While Debt-to-Assets, Size, and Return on Equity perform clearly worse. This is remarkable as the Price Momentum was not significantly influenced by any of the indicators in the VAR model.

Comparing both the VAR models to the buy-and-hold different styles come forward as good performing. These styles benefit from the information given by the chosen macro indicators. Book-to-Price, Analyst Revisions, and Beta have a better Sharpe ratio when being timed through the VAR structure, while Earning Yield, Dividend Yield, and Free Cash Flow perform less. The good performing styles are significantly influenced by at least two macro indicators in the VAR model. While the other three are influences by none or one macro indicator. Analyst Revisions, Book-to-Price, and Beta styles clearly benefit through this parametric model. Price Momentum, Return on Equity, Debt-to-Assets and Size perform roughly the same.

Comparing the non-parametric JPM indicator results to the parametric VAR and MS-VAR results, the JPM indicator based strategy performs good due to high weights in the rewarding FCF and Analyst Revision styles. Only the FCF Sharpe ratio is clearly better than those of parametric strategies, but is worse than the buy-and-hold. Other Sharpe ratios are not particularly higher than with other strategies. The better JPM mean performance is due to higher investments in the winning styles rather than a better timing.

6 Conclusion

In this paper I aim to construct a parametric model to time the Eurozone macro-economic cycle and use this cycle output as the basis for an investment strategy. This model aims to improve upon the style timing performance of non-parametric based models several brokers use. The parametric models I use are a regular VAR model and an MS-VAR model as first extensively described by Krolzig [2003a]. This model combines information from six different macro-economic variables relevant to the Eurozone to estimate the probability of a recession at each point in time. The MS-VAR model also compiles a trading strategy by altering weights for ten different styles using this probability and the values of the macro-economic input series. The regular VAR model only uses the latter as input.

The broker models I review use different Eurozone macro-economic indicators and compiling methods to construct an economic cycle indicator. This indicator divides the economy in four regimes rather than two as the MS-VAR model does. Depending on the mean and variance of each of the ten styles during each regime an investment weight is given for each of these styles for the coming period. Co-movements of the different styles are hereby ignored to assess individual style performance and sensitivity to timing. The MS-VAR uses two sets of parameters for each of the two regimes. It calculates the expected returns and the expected variances for all styles for both regimes and weights them according to the probability each regime will occur. Also the MS-VAR and VAR models ignore co-movements in calculating the investment weights. Furthermore, the MS-VAR and VAR have a more autoregressive nature, while the broker models use only today's information to indicate the regime.

I compare all models in terms of the cumulative returns of their investment strategy using a portfolio of the ten styles. I also compare the regimes they indicate to the official CEPR Eurozone recession dates. I find that none of the models are really close to the official CEPR peak and trough dates in the economy. Most of the indicators miss the turning points by more than six months, although one month of this lag is by construction. Only the JP Morgan indicator seems to score reasonable in indicating the turning points being only two months off on average. The MS-VAR however is only spot on once while being ten months off in the other cases although it has less false peaks and troughs compared to the brokers. All models, except the GDP-based Nomura indicator, signal the crisis following the tech bubble as a recession, while it officially was never qualified as such. However, with respect to macro-economic cycle research the short sample prevents any hard conclusions on indication performance.

When comparing the three broker models to a buy-and-hold benchmark I find that none of them perform better in terms of the Sharpe ratio but all do in terms of mean return. When looking at the individual styles only Analyst Revisions improves in terms of the Sharpe ratio for the JPM model when style timing is included in the model. Earnings Yield, Dividend Yield, Free Cash flow, Analyst Revisions, Price Momentum and Return on Equity improve only in terms of the mean return when style timing is used to calculate weights, while the Sharpe ratio's stay about the same.

Applying an MS-VAR to the macro-economy brings several problems. The data availability poses a problem for clear outcome interpretation of the estimated parameters. Due to the low number of recessions since 1993 the recessionary part of the model is overfitted and therefore estimates incorrect parameters and standard errors, making interpretation cumbersome. If a regular VAR is estimated overfitting poses no problem anymore and more parameters become significant. These VAR results are used to interpret the MS-VAR results indirectly but qualitatively. The fact that the parameters in the VAR model are significant does indicate that it can be useful to include macro indicators in style timing. The Markov Switching however contributes little to nothing at this point in time since more 'recessions' are needed in the data set. MS-VAR models currently have more use in stock market modelling than in macro-economic cycle modelling.

The relevant macro indicators based on the VAR estimation are the M1, ESX, ESI, and CLI. They are important for both constructing expected returns for the styles as well as indicating regimes of the MS-VAR. Opposed to the IIP and the EPS indicator series which only add information for the regime switches and less directly to style performance. Both the MS-VAR and VAR perform better than the buy-and-hold benchmark but worse than the JP Morgan indicator. Style timing based strategies outperform a buy-and-hold benchmark for the European market. However the rule based non-parametric model performs better than the parametric models. Whether this less performance of the parametric model is mainly due to the small data set is hard to say. Although the styles which are influenced significantly by two or more macro-indicators in the VAR model are performing better than in the JPM model. This is a strong indication that for some styles, style timing with the use of macro indicators in a parametric model works.

I do find that VAR and MS-VAR performance are highly alike, but the MS-VAR performs slightly better overall although not significantly. Thus the added value of Markov switching parameters is minimal. This is also backed up when looking at the styles individually. Comparing the VAR results with the MS-VAR results shows again that the Beta and Price Momentum styles improve in terms of the Sharpe ratio when different regimes are included in the model. The Price Momentum style is however not significantly influenced by any of the macro-indicators in the VAR model, so that this improvement is caused by the regime switching is questionable. Influence of macro-economic regime switching on the styles should also be checked with a model without an overfitted recession regime.

My results imply that the simple rule based style timing models that brokers use for timing the Eurozone economy cannot be improved upon by implementing a VAR or MS-VAR model for timing the economy. At least not with a 22 year data set. Investing based on the macro-economic regime indication of the J.P.Morgan indicator yields the best performance for the European market in the period 2001 to 2016.

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A Data Sources, Availability and Summary

A.1 Data sources and availability

Indicator	Sample start	Sample End	Source	Availability lag
Composite Leading Indicator	Jan 1966	Feb 2016	OECD	13th of next month
France bond yield	Jan 1960	Mar 2016	Datastream	1st day of the next month
UK bond yield	Jan 1963	Mar 2016	Datastream	1st day of the next month
Germany bond yield	Jan 1957	Mar 2016	Datastream	1st day of the next month
Germany IFO	Jan 1991	Apr 2016	Datastream	25th of the month
Producer Price Index	Jan 1981	Mar 2016	Eurostat	2nd day of the 2nd next month
Earnings per Share revisions	Dec 1993	Apr 2016	Factset	1st day of the 2nd next month

Table 19: BAML data

Indicator	Sample start	Sample End	Source	Availability lag
M1 Money Supply	Jan 1970	Feb 2016	OECD	27th next month
Composite Leading Indicator	Jan 1966	Feb 2016	OECD	13th of next month
France bond yield	Jan 1960	Mar 2016	Datastream	1st day of the next month
UK bond yield	Jan 1963	Mar 2016	Datastream	1st day of the next month
Germany bond yield	Jan 1957	Mar 2016	Datastream	1st day of the next month
Germany IFO	Jan 1991	Apr 2016	Datastream	25th of the month
SEK/USD exchange rate	Jan 1971	Apr 2016	FRED St. Louis	0 (daily data)
Earnings per Share revisions	Dec 1993	Apr 2016	Factset	1st day of the 2nd next month

Table 20: JPM data

Indicator	Sample start	Sample End	Source	Availability lag
GDP Europe	Q2 1995	Q4 2015	OECD	3 months
Economic Sentiment Indicator	Jan 1989	Apr 2016 2016	Eurostat	27th of the month

Table 21: Nomura data

Indicator	**Sample start**	**Sample End**	**Source**	**Availability lag**
Industrial production	Jul 1975	Feb 2016	OECD	1.5 months
France bond yield	Jan 1960	Mar 2016	Datastream	1st day of the next month
UK bond yield	Jan 1963	Mar 2016	Datastream	1st day of the next month
Germany bond yield	Jan 1957	Mar 2016	Datastream	1st day of the next month
SEK/USD exchange rate	Jan 1971	Apr 2016	FRED St. Louis	0 (daily data)
M1 Money Supply	Jan 1970	Feb 2016	OECD	27th next month
Earnings per Share revisions	Dec 1993	Apr 2016	Factset	1st day of the 2nd next month
Composite Leading Indicator	Jan 1966	Feb 2016	OECD	13th of next month
Economic Sentiment Indicator	Jan 1989	Apr 2016 2016	Eurostat	27th of the month
Index of Housing Permits	Jan 1995	Jan 2016	Eurostat	4 months
Eurostoxx stock price index	Jan 1987	Mar 2016	Datastream	1st day of the next month
M2 Euro area	Jan 1980	Mar 2016	Datastream	Last day of the next month

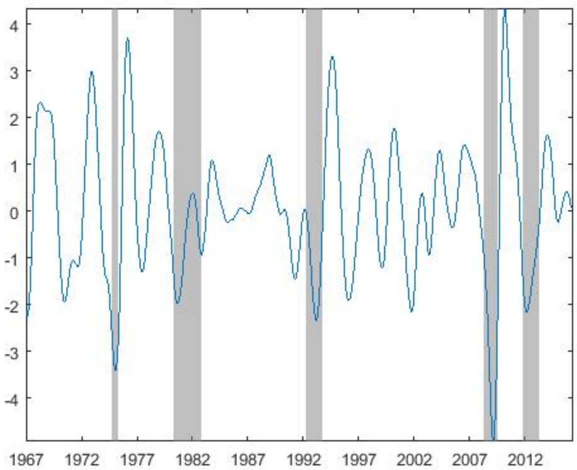
Table 22: MS-VAR data

Peak/trough	**Date**	**Announcement date**
Peak	Q3 1974	22 Sep 2003
Trough	Q1 1975	22 Sep 2003
Peak	Q1 1980	22 Sep 2003
Trough	Q3 1982	22 Sep 2003
Peak	Q1 1992	22 Sep 2003
Trough	Q3 1993	22 Sep 2003
Peak	Q1 2008	31 Mar 2009
Trough	Q2 2009	4 Oct 2010
Peak	Q3 2011	15 Nov 2012
Trough	Q1 2013	1 Oct 2015

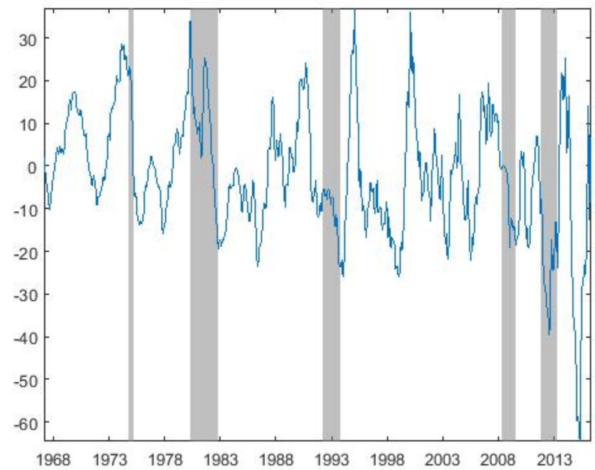
Table 23: CEPR dates

A.2 Descriptive statistics

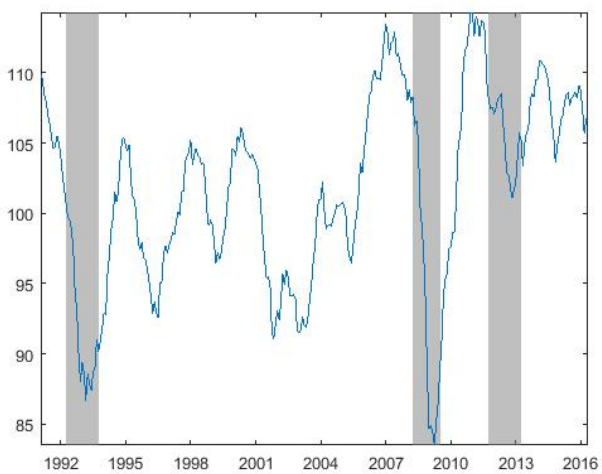
A.2.1 BAML indicators



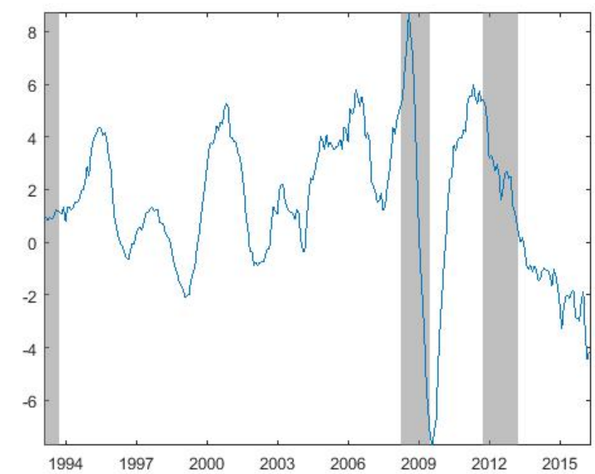
(a) CLI 12-month change (%)



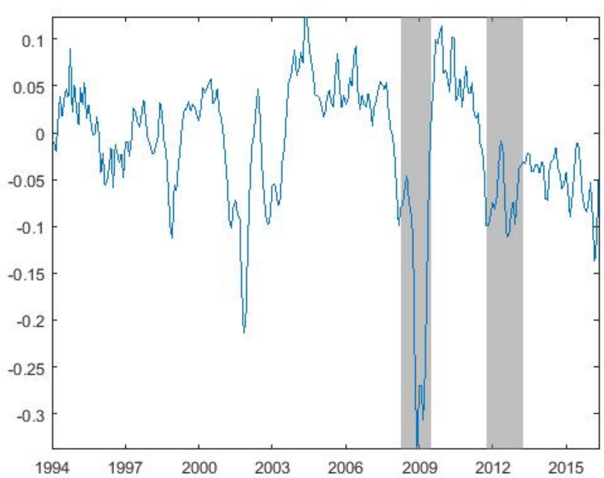
(b) EU bond yield (Fr, UK, BD) 12-month change (%)



(c) German IFO Indicator



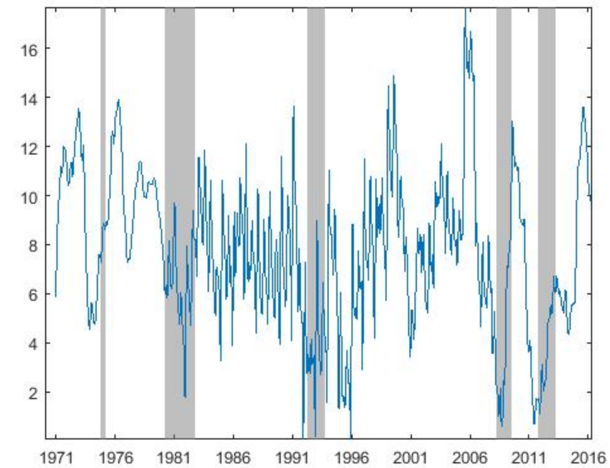
(d) Producer Price Index 12-month change (%)



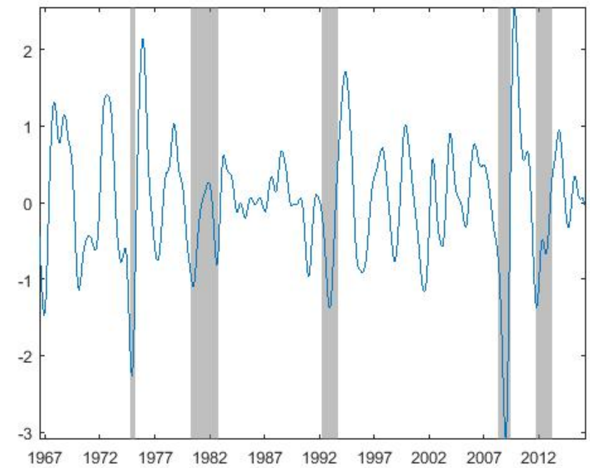
(e) EPS revision ratio

Figure 9: BAML indicator series (Grey area mark CEPR recessions)

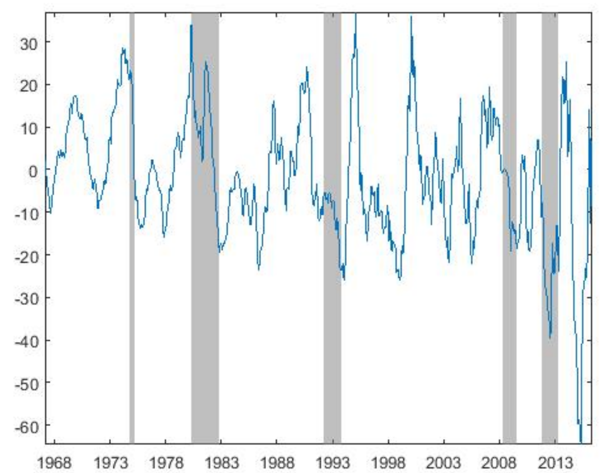
A.2.2 JPM indicators



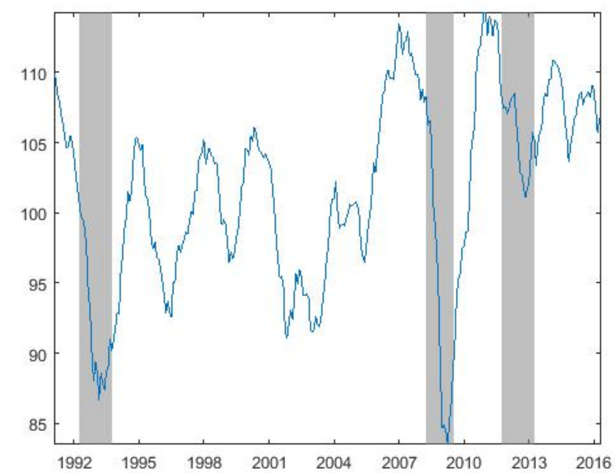
(a) EU Money supply (M1) 12-month change (%)



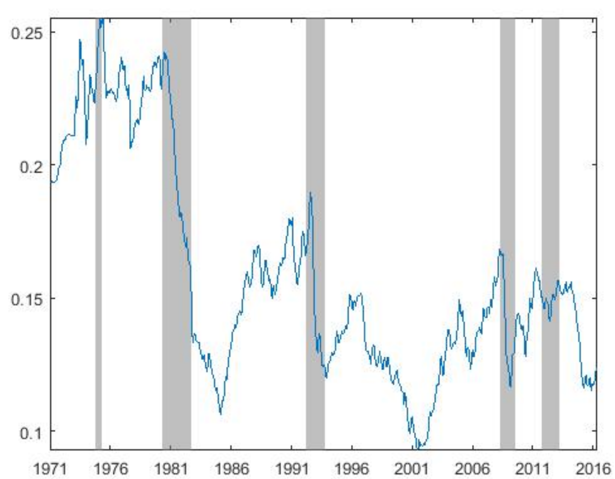
(b) CLI 6-month change (%)



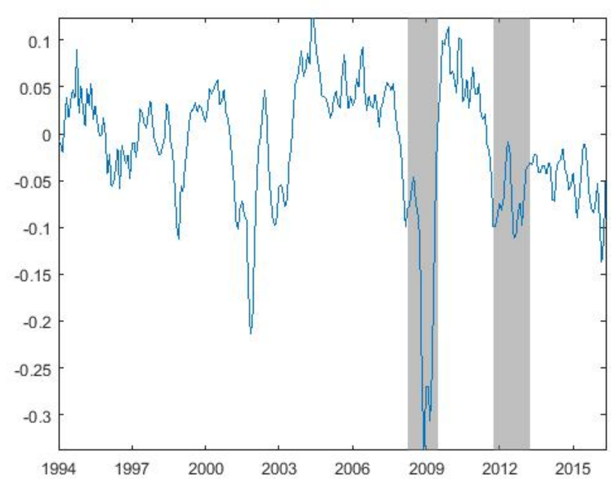
(c) EU bond yield (Fr, UK, BD) 12-month change (%)



(d) German IFO Indicator



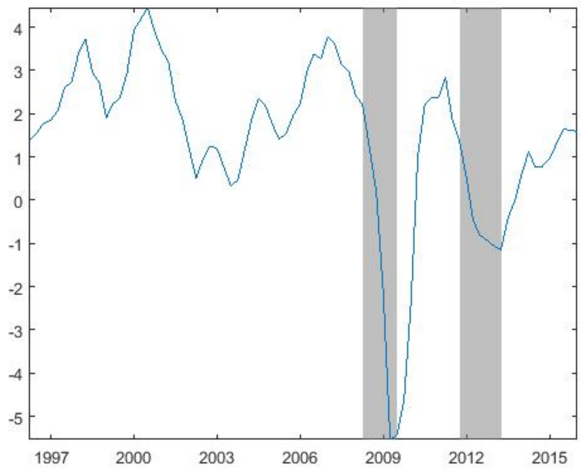
(e) USD/SEK exchange rate



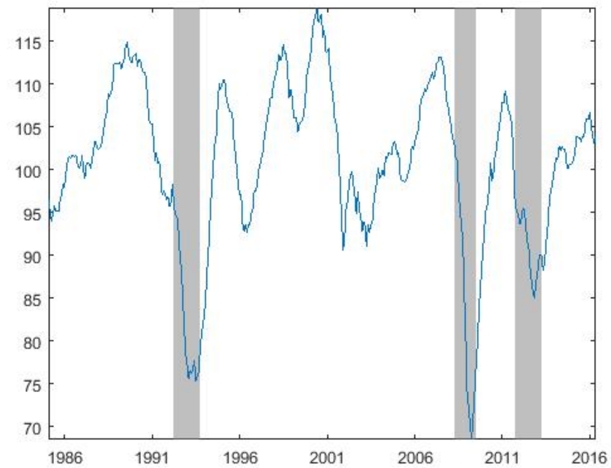
(f) EPS revision ratio

Figure 10: JPM indicator series (Grey area mark CEPR recessions)

A.2.3 Nomura indicators



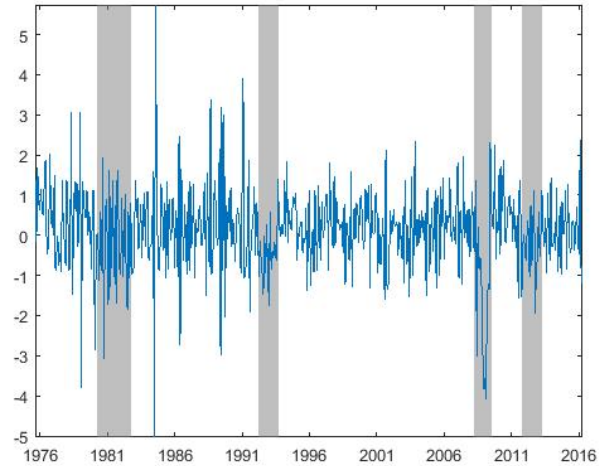
(a) EU GDP 12-month change (%)



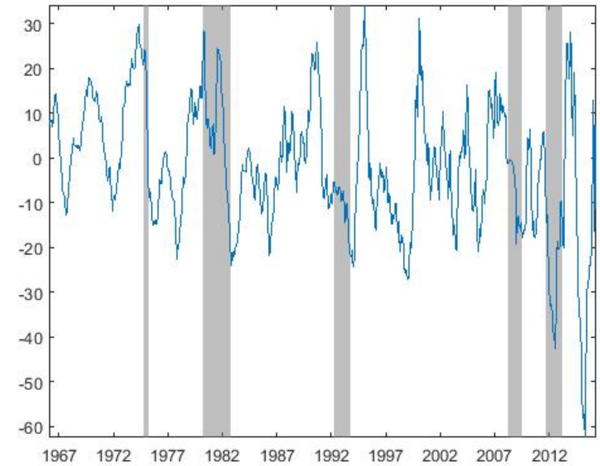
(b) EU Econimic Sentiment Indicator (%)

Figure 11: Nomura indicator series (Grey area mark CEPR recessions)

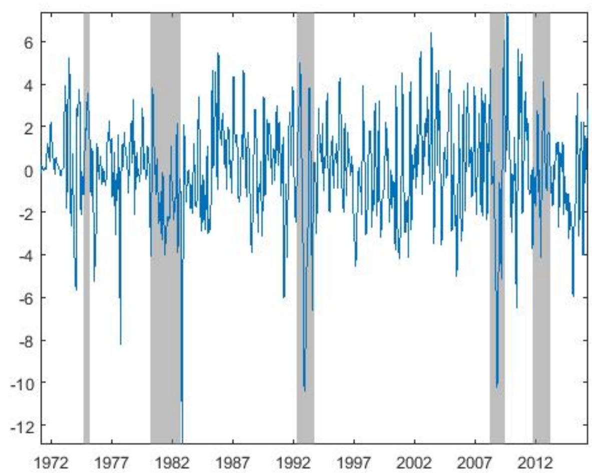
A.3 Markov switching model macro-economic variables



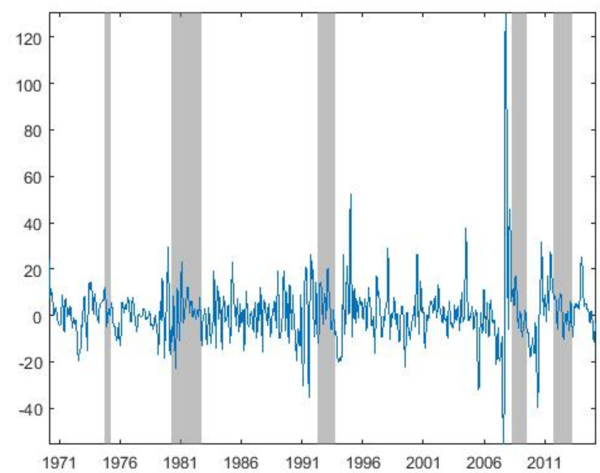
(a) IIP 1-month change (%)



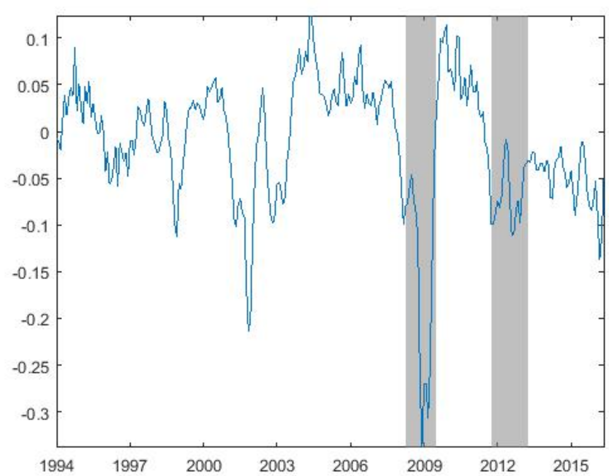
(b) EU bond yield (Fr, UK, BD) 12-month change (%)



(c) SEK/USD exchange rate 1-month change (%)

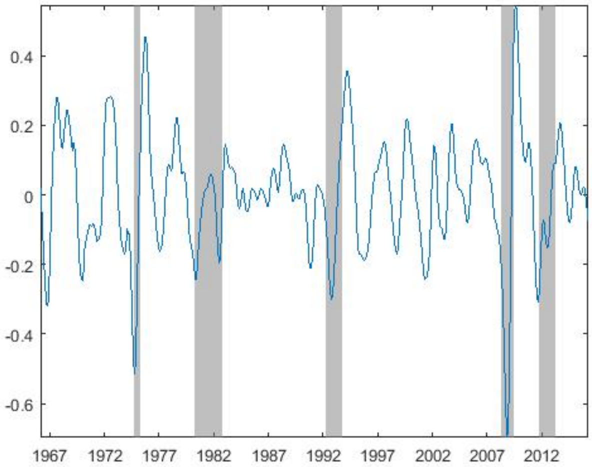


(d) M1 money supply 1-month change (%) of 12-month change

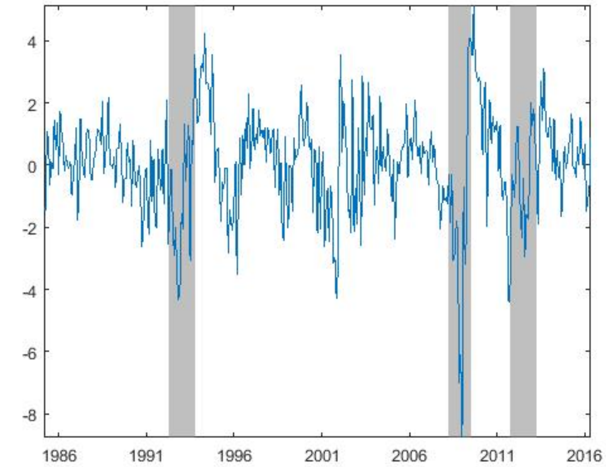


(e) Earnings per share revisions

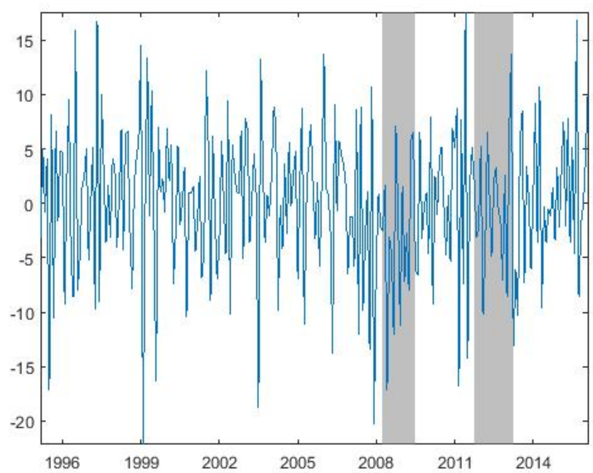
Figure 12: MS-VAR indicator series (Grey area mark CEPR recessions)



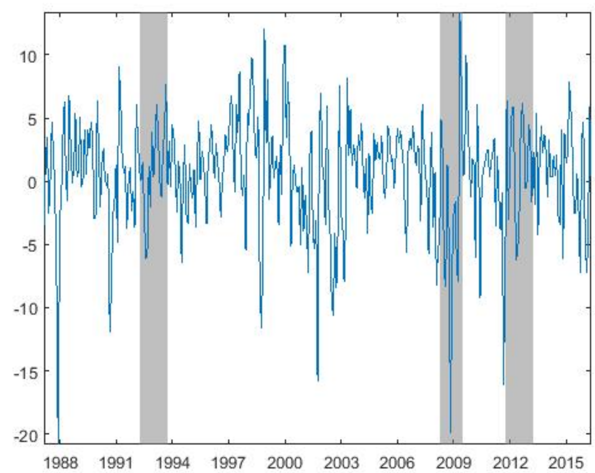
(a) Composite Leading Indicator 1-month change (%)



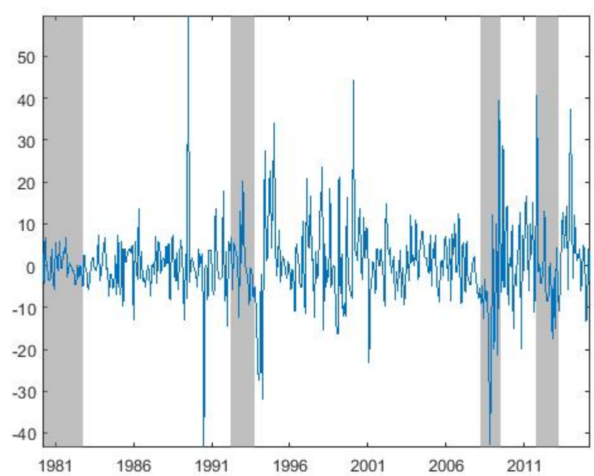
(b) Economic sentiment indicator 1-month change (%)



(c) Housing permits granted 1-month change (%)



(d) Eurostoxx



(e) M2 money supply 1-month change (%) of 12-month change

Figure 13: MS-VAR indicator series (Grey area mark CEPR recessions)

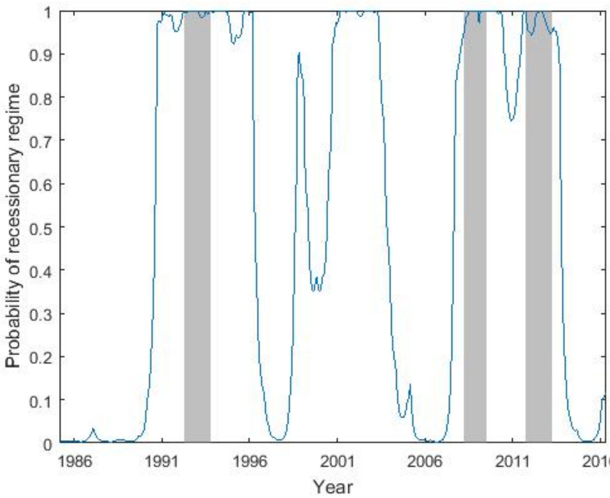
A.3.1 Markov switching of univariate input variables

Variable	ESI	CLI	Housing	Eurostoxx	M2 Money
ν_0	**0.2800**	**−0.0171**	0.6186	**1.2344**	-0.3142
	(0.0734)	(0.0014)	(0.7586)	(0.2591)	(0.3280)
σ_0	0.7517	0.0245	2.3931	1.6586	2.2258
	(0.0597)	(0.0008)	(0.7125)	(0.2055)	(0.2446)
ϕ_0	**0.1876**	**1.0003**	**−0.3961**	0.1018	**−0.0146**
	(0.0728)	(0.0054)	(0.1031)	(0.0899)	(0.0575)
ν_1	-0.1025	**0.0433**	-1.6655	-0.5443	1.6228
	(0.1427)	(0.0053)	(2.9496)	(0.6000)	(1.5134)
σ_1	3.0916	0.0365	2.8686 *	2.3859	3.9538
	(0.0847)	(0.0017)	(2.4714)	(0.3075)	(0.8014)
ϕ_1	**0.5853**	**0.9292**	-0.3106	**0.3259**	0.0886
	(0.0505)	(0.0124)	(0.1914)	(0.1018)	(0.1060)
p_{00}	0.9723	0.9461	0.9539	0.9412	0.9452
	(0.0185)	(0.0181)	(0.0728)	(0.0284)	(0.0205)
p_{11}	0.9753	0.9461	0.8712	0.9199	0.8879
	(0.0147)	(0.0580)	(0.1681)	(0.0399)	(0.0365)
ζ	1	1	1	0	1
L_{MSW}	-635.5	1227.8	-829.2	-989.8	-1480.2
k	30	46	227	82	86

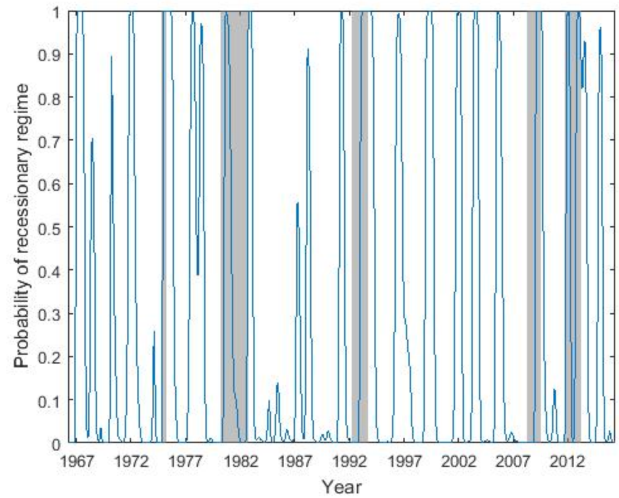
Table 24: Univariate MS-VAR indicator parameters. Standard errors of the parameters are given in the brackets below. For the intercepts and autoregressive parameters, the significant parameters at a 5% level are bold.

Variable	IIP	Bond	USD/SEK	M1 Money	EPS Revisions
ν_0	**0.2085**	-0.0278	0.1113	-0.5688	-0.1340
	(0.0426)	(0.1496)	(0.1263)	(0.3455)	(0.1562)
σ_0	0.9177	1.6385	1.2991	2.4906	1.4911
	(0.0376)	(0.1303)	(0.1328)	(0.2658)	(0.1375)
ϕ_0	**−0.2876**	**0.9862**	**0.3215**	**0.4776**	**0.9157**
	(0.0474)	(0.0102)	(0.0714)	(0.0414)	(0.0273)
ν_1	-0.3750	-0.1009	-0.2126	4.4538	0.1013
	(0.4890)	(0.5270)	(0.2523)	(2.7407)	(3.3327)
σ_1	1.5504	2.6584	1.7199	4.7566	2.4596
	(0.3859)	(0.3588)	(0.1856)	(0.7834)	(1.2766)
ϕ_1	-0.1029	**0.9075**	**0.4077**	**0.4164**	**0.9327**
	(0.1442)	(0.0301)	(0.0786)	(0.0467)	(0.1627)
p_{00}	0.9750	0.9389	0.9359	0.9449	0.9861
	(0.0131)	(0.0197)	(0.0286)	(0.0160)	(0.0172)
p_{11}	0.7268	0.8741	0.9098	0.7837	0.8747
	(0.1346)	(0.0405)	(0.0194)	(0.0556)	(0.1172)
ζ	1	0	1	0	1
L_{MSW}	-681.9	-1707.7	-1207.5	-1976.2	-633.2
k	48	113	280	99	46

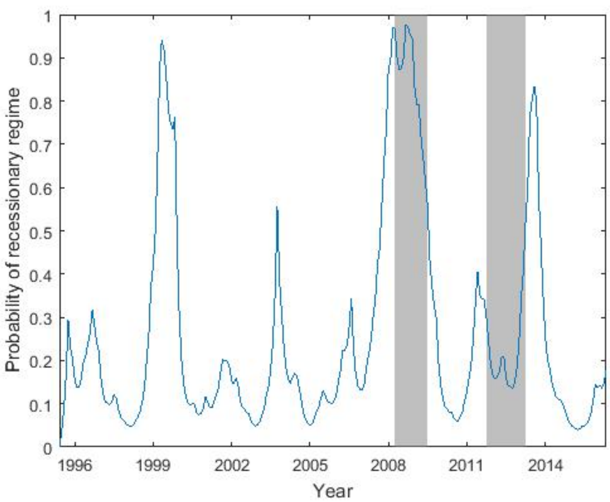
Table 25: Univariate MS-VAR indicator parameters. Standard errors of the parameters are given in the brackets below.



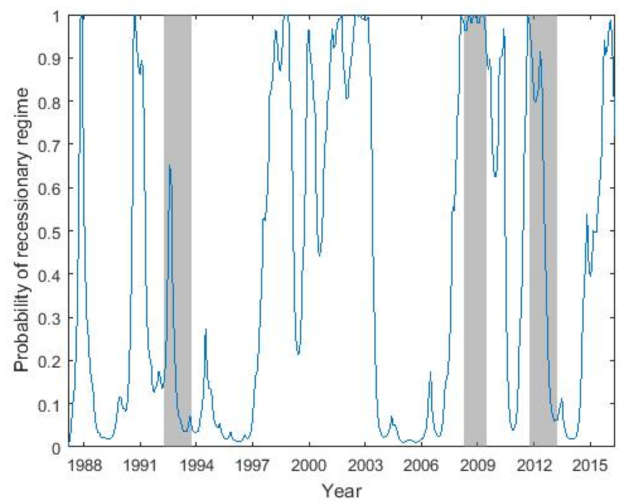
(a) ESI



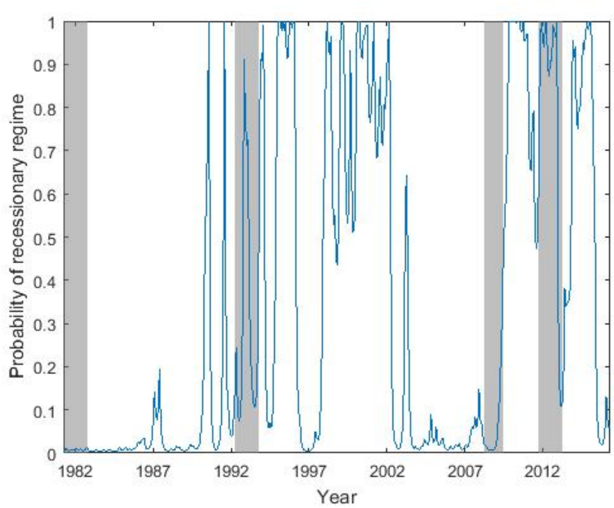
(b) CLI



(c) Housing permits

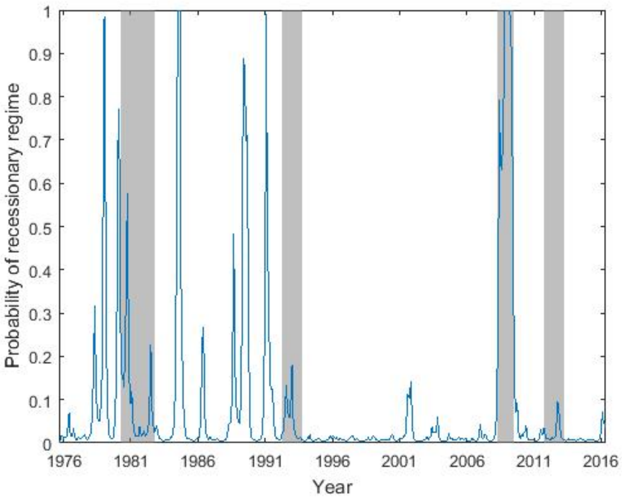


(d) Eurostoxx

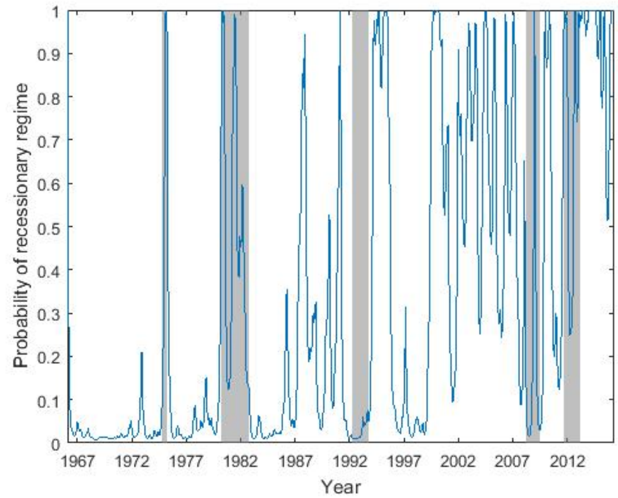


(e) M2 money supply

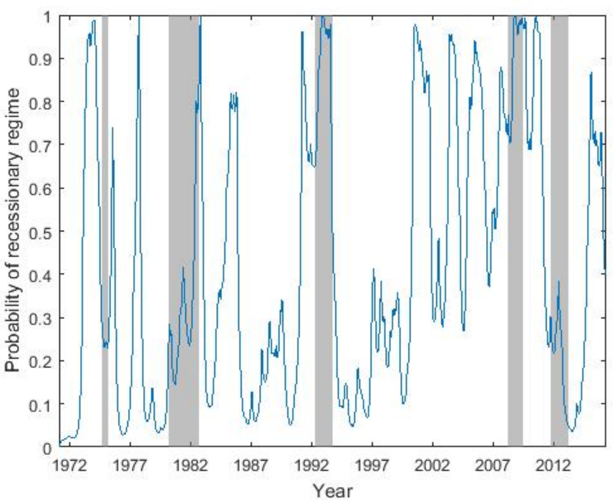
Figure 14: Regime probabilities of indicators with recessions as grey areas



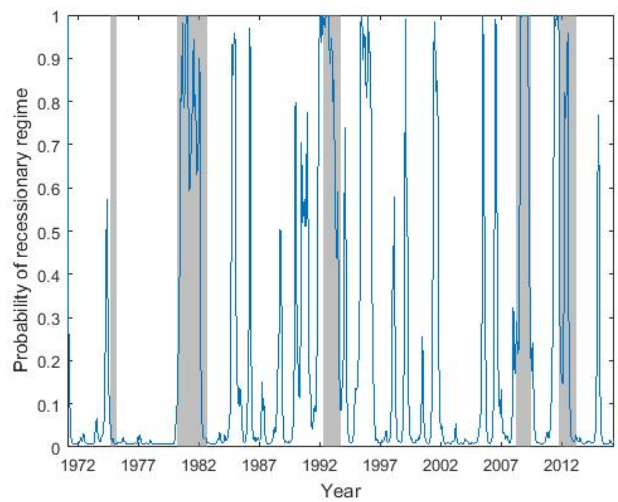
(a) IIP



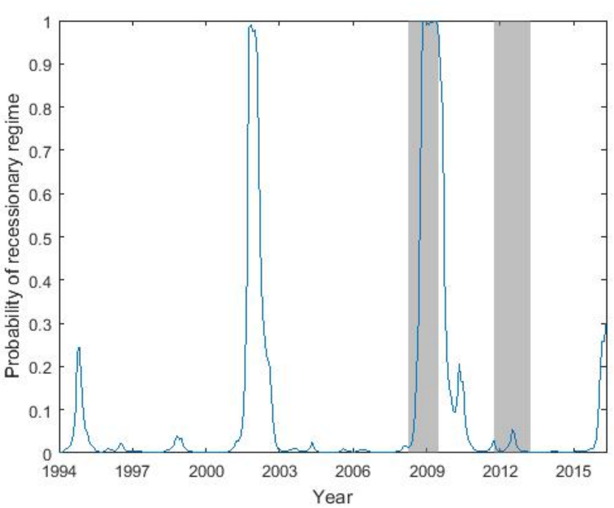
(b) EU bond yield (Fr, UK, BD) 12-month change (%)



(c) USD/SEK exchange rate 1-month change (%)



(d) M1 money supply



(e) Earnings per share revisions

Figure 15: Regime probabilities of indicators with recessions as grey areas

A.4 Estimated parameter value MS-VAR without leading indicators

In this section the parameter values of the MS-VAR model without leading indicators are presented. This means that the Composite Leading indicator (CLI) and the Earnings per Share (EPS) are omitted from the model. Also the influence of only the coincident indicators on the investments styles is not within the scope of this thesis.

$$\begin{pmatrix} IIP \\ M1 \\ ESX \\ ESI \end{pmatrix} \qquad \mathcal{V}_0 = \begin{pmatrix} \mathbf{0.216} & (0.055) \\ -0.401 & (0.629) \\ \mathbf{0.724} & (0.292) \\ 0.115 & (0.099) \end{pmatrix}, \mathcal{V}_1 = \begin{pmatrix} 0.307 & (2.399) \\ 12.501 & (77.421) \\ -3.559 & (6.137) \\ -1.106 & (2.626) \end{pmatrix},$$

$$\begin{pmatrix} IIP \\ \\ M1 \\ \\ ESX \\ \\ ESI \end{pmatrix} \qquad \phi_{0,y,y} = \begin{pmatrix} \mathbf{-0.381} & \mathbf{-0.014} & 0.015 & \mathbf{0.143} \\ (0.062) & (0.005) & (0.013) & (0.031) \\ 0.452 & \mathbf{0.482} & 0.216 & -0.837 \\ (0.798) & (0.053) & (0.159) & (0.444) \\ \mathbf{-0.846} & 0.041 & \mathbf{0.232} & 0.220 \\ (0.400) & (0.028) & (0.067) & (0.188) \\ 0.168 & 0.001 & \mathbf{0.047} & \mathbf{0.434} \\ (0.135) & (0.011) & (0.023) & (0.058) \end{pmatrix},$$

$$\begin{pmatrix} IIP \\ \\ M1 \\ \\ ESX \\ \\ ESI \end{pmatrix} \qquad \phi_{1,y,y} = \begin{pmatrix} 0.031 & -0.011 & -0.052 & 0.538 \\ (1.005) & (0.056) & (0.432) & (1.727) \\ 0.554 & 0.576 & 2.584 & -3.014 \\ (33.931) & (1.014) & (6.654) & (34.246) \\ -1.119 & -0.083 & -0.117 & 0.245 \\ (3.204) & (0.327) & (2.497) & (5.803) \\ 0.136 & -0.025 & 0.039 & 0.233 \\ (1.937) & (0.148) & (0.682) & (1.572) \end{pmatrix},$$

$$\Sigma_0 = \begin{pmatrix} 0.484 & 0.619 & 0.131 & 0.188 \\ 0.619 & 58.966 & 2.608 & -0.053 \\ 0.131 & 2.608 & 14.529 & 0.843 \\ 0.188 & -0.053 & 0.843 & 1.692 \end{pmatrix},$$

$$\Sigma_1 = \begin{pmatrix} 1.065 & 0.352 & 0.015 & -0.167 \\ 0.352 & 1237.528 & -17.418 & -1.173 \\ 0.015 & -17.418 & 39.621 & 9.372 \\ -0.167 & -1.173 & 9.372 & 4.609 \end{pmatrix},$$

$$p_{00} = 0.967(0.028), \quad p_{11} = 0.687(0.190), \quad \hat{L} = -2469.0, \quad \text{BIC} = 5237.5 \quad .$$

B MS-VAR Estimation

MS-VAR one common cycle

The structure of the MS-VAR as I derive and define it is largely based on the structure for the MSIAH-VAR in the book of Krolzig [1997]. As mentioned in the main report I use only two economic regimes and one time lag. Furthermore I allow for regime dependent heteroskedasticity and regime dependent autoregressive parameters. The regime changes are incorporated via a change in and intercept term rather than an in the mean. In Section B.6 a summary of definitions, sizes and formulas can be found.

B.1 Model definition

The model with K indicator series as input in this subsection is defined as:

$$y_t = \boldsymbol{\nu}_m + \Phi_m y_{t-1} + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(0, \Sigma_m), \tag{9}$$

where $m \in \{0,1\}$, y_t is the $(1 \times K)$ vector of observations for time t, Φ is a $(K \times K)$ matrix of autoregressive parameters, ν_m is a $(1 \times K)$ vector of intercepts dependent on the regime at t and ϵ_t is a $(1 \times K)$ vector of shocks. The shocks are not correlated over time but contemporaneous correlation is allowed. The contemporaneous correlation and shock variances are also regime dependent.

In matrix form with the matrices defined as in Section B.6.

$$y_t = B_m x_t + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(0, \Sigma_m), \tag{10}$$

Furthermore the model follows an unobservable Markov process with two possible regimes, $s_t = 0$ for a expanding regime and $s_t = 1$ for a recessionary regime. These regimes follow a Markov chain with transition probabilities which are defined as

$$p_{ij} = \Pr[s_t = j | s_{t-1} = i], \text{ with } i, j \in \{0,1\} \quad . \tag{11}$$

The transition probabilities for each departure state should add up to 1. So $p_{00} + p_{01} = 1$ and $p_{10} + p_{11} = 1$, so p_{00} and p_{11} are the only two free parameters in the binary case. These transitions can be gathered in a regime transition probability matrix,

$$\boldsymbol{P} = \begin{pmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{pmatrix}. \tag{12}$$

Last aspect to define is the initial regime of s_1 at $t = 1$. I define,

$$\zeta = \Pr[s_1 = 0] \quad , \tag{13}$$

There are only two possible states in one timestep thus it automatically is true that $\Pr[s_1 = 1] = 1 - \zeta$. The state probability vector for the first timestep is thus $\xi_{1|0} = (\zeta,\ (1-\zeta))'$. This starting regime is also unknown and therefore ζ is a separate parameter to estimate.

Since the process S_t is latent the real regime is unobservable. Based on the information from the data of present and past observations it is possible to make and inference on $\Pr[S_t = s_1 | y_t, y_{t-1}, ..., y_1]$ making use of Bayes' rule,

$$\Pr[A|B] = \frac{\Pr[B|A]\Pr[A]}{\Pr[B]} \quad ,$$

which will be explained used in the following section.

B.2 Filtering

First let η_t be the vector of densities of y at t given the state ξ_t at t and all the previous data Y_{t-1}. With $M = 2$ regimes

$$\eta_t = \begin{bmatrix} p(y_t|\xi_t = \iota_0, Y_{t-1}) \\ p(y_t|\xi_t = \iota_1, Y_{t-1}) \end{bmatrix} = \begin{bmatrix} (2\pi)^{-\frac{K}{2}}|\Sigma_0|^{-\frac{1}{2}}e^{\{-\frac{1}{2}(y_t - B_0x_t)'\Sigma_0^{-1}(y_t-B_0x_t)\}} \\ (2\pi)^{-\frac{K}{2}}|\Sigma_1|^{-\frac{1}{2}}e^{\{-\frac{1}{2}(y_t - B_1x_t)'\Sigma_1^{-1}(y_t-B_1x_t)\}} \end{bmatrix} \quad . \tag{14}$$

Then the inference $\hat{\xi}_{t|t}$ is given by

$$\hat{\xi}_{t|t} = \frac{\eta_t \odot \hat{\xi}_{t|t-1}}{\mathbf{1}'_M(\eta_t \odot \hat{\xi}_{t|t-1})}, \tag{15}$$

where $\odot$ stands for element by element multiplication. Then the forecast probabilities $\hat{\xi}_{t+1|t}$ are given by

$$\hat{\xi}_{t+1|t} = \mathbf{P}'\hat{\xi}_{t|t}. \tag{16}$$

Then I iterate trough these two steps starting with the deterministic starting values of $\hat{\xi}_{1|0}$, which is a $(1 \times M)$ state vector and is defined in the previous section.

B.3 Smoothing

To use all all available information to full extend a smoothing filter is also applied. This filter starts with $\hat{\xi}_{T|T}$ which is the inference at time T and then iterating back to $t = 1$ via

$$\hat{\xi}_{t|T} = (\mathbf{P}(\hat{\xi}_{t+1|T} \oslash \hat{\xi}_{t+1|t})) \odot \hat{\xi}_{t|t} \quad , \tag{17}$$

where $\oslash$ stands for dividing element by element

B.4 Estimation

Now the smoothed probabilities are used to estimate the parameters for the next iteration. This process of filtering, smoothing and estimation is repeated until a certain level of convergence is reached and the log-likelihood does not increase more than a certain threshold. The conditional log-likelihood can be calculated as a byproduct of the filter recursion and is equal to

$$\ell(y_1, y_2, ..., y_T; \boldsymbol{\lambda}) = \sum_{t=1}^{T} \log(\eta_t' \boldsymbol{\xi}_{t|t-1}) \quad . \tag{18}$$

This log-likelihood is used to calculate the likelihood of a certain parameter set, $\hat{\lambda}$. For estimation of the parameters another closed form solution is used and is defined as

$$\begin{aligned} L = (\lambda|Y) &= \int p(Y, \xi|\lambda)\, d\xi \\ &= \int p(Y|\xi, \theta)\ \Pr(\xi|\rho, \xi_0)\, d\xi. \end{aligned} \tag{19}$$

Where $\lambda = (\theta, \rho, \zeta)$ and θ is a vector containing the VAR parameters, ρ a vector with the transition probabilities, and ζ as defined in (13). Furthermore by definition

$$p(Y|,\theta) = \prod_{t=1}^{T} p(y_t|\xi_t, Y_{t-1}, \theta),$$

$$\Pr(\xi|\rho, \xi_0) = \prod_{t=1}^{T} \Pr(\xi_t|\xi_{t-1}, \rho).$$

The estimators of the parameters are given below, the matrix definitions can be found in Section B.6. This is last step op the EM-algorithm, the set of parameters estimated by these formulas are use as input formulas (12), (13), and (14) for the next iteration.

The estimator for B'_m is given by

$$\tilde{B}'_m = (\bar{\mathbf{X}}'\hat{\Xi}_m\bar{\mathbf{X}})^{-1}\bar{\mathbf{X}}'\hat{\Xi}_m\mathbf{Y}. \tag{20}$$

The estimator of Σ_m is given by

$$\tilde{\Sigma}_m = \hat{T}_m^{-1}\tilde{\mathbf{U}}'_m\hat{\Xi}_m\tilde{\mathbf{U}}_m \quad . \tag{21}$$

Next estimating p_{00} and p_{11}. Let

$$\tilde{p}_{ij,t+1} = \Pr[S_{t+1} = j, S_t = i|\mathcal{Y}_T; \boldsymbol{\theta}^{(k-1)}] = p_{ij}^{(k-1)}\xi_{t|t,i} \cdot \frac{\xi_{t+1|T,j}}{\xi_{t+1|t,j}}. \tag{22}$$

Then the derivative of p_{00}

$$\begin{aligned}\frac{\partial \ell_{EM}(\mathcal{Y}_T; \boldsymbol{\theta}, \boldsymbol{\theta}^{(k-1)})}{\partial p_{00}} &= \frac{\partial \sum_{t=2}^{T} \tilde{p}_{00,t}\log(p_{00}) + \tilde{p}_{01,t}\log(1-p_{00})}{\partial p_{00}} \\ &= \sum_{t=2}^{T}(\frac{\tilde{p}_{00,t}}{p_{00}} - \frac{\tilde{p}_{01,t}}{1-p_{00}}).\end{aligned} \tag{23}$$

Setting this to zero gives

$$p_{00}^{(k)} = \frac{\sum_{t=2}^{T} \tilde{p}_{00,t}}{\sum_{t=2}^{T}(\tilde{p}_{00,t} + \tilde{p}_{01,t})} \tag{24}$$

The same can be done for p_{11}. Finally estimating ζ

$$\begin{aligned}\frac{\partial \ell_{EM}(\mathcal{Y}_T; \boldsymbol{\theta}, \boldsymbol{\theta}^{(k-1)})}{\partial \zeta} &= \frac{\partial(\xi_{1|T,0}\log(\zeta) + \xi_{1|T,1}\log(1-\zeta))}{\partial \zeta} \\ &= \frac{\xi_{1|T,0}}{\zeta} - \frac{\xi_{1|T,1}}{1-\zeta}.\end{aligned} \tag{25}$$

Setting this expression to zero gives

$$\tilde{\zeta}^{(k)} = \xi_{1|T,0}^{(k-1)} \tag{26}$$

B.5 h-Scores

After the algorithm above is ended, the h-scores are constructed in order to obtain standard errors for the parameters. Let $\tilde{\theta} = (\text{vec}(\tilde{B}_0), \text{vec}(\tilde{B}_1), \text{vec}(\tilde{\Sigma_0}), \text{vec}(\tilde{\Sigma_1}))'$ be the vector of estimated VAR parameters and let $\tilde{\rho} = (p_{00}, p_{11})'$. These two vector are combined in vector λ which is therefore a $((2(K \cdot (K+1) + \frac{1}{2}(K^2+K)) + M) \times 1)$-vector. Now define,

$$h_t(\lambda) = \frac{\partial \ln p(y_t | Y_{t-1}; \lambda)}{\partial \lambda} \quad . \tag{27}$$

Hamilton and Perez-Quiros [1996] show that the scores can be calculated using the following recursion.

$$h_t(\tilde{\lambda}) = \Psi_t(\tilde{\lambda})' \hat{\xi}_{t|t} + \sum_{\tau=1}^{t-1} \Psi_\tau(\tilde{\lambda})' (\hat{\xi}_{\tau|t} - \hat{\xi}_{\tau|t-1}) \quad , \tag{28}$$

wherein

$$\Psi_\tau(\tilde{\lambda}) = \frac{\partial \ \text{diag}(\eta_\tau)\mathbf{P'}}{\partial \lambda'}, \tag{29}$$

which is the partial derivative of the likelihood function to each parameter in λ. I conduct this differentiation numerically for each parameter. The smoothed probabilities $\hat{\xi}_{\tau|t}$ can be derived the same way as the smoothed probabilities before

$$\hat{\xi}_{\tau|t} = (\mathbf{P}(\hat{\xi}_{\tau+1|t} \oslash \hat{\xi}_{\tau+1|t})) \odot \hat{\xi}_{\tau|\tau}. \tag{30}$$

The scores should add up to zero, $\sum\limits_{t=1}^{T} h_t(\tilde{\lambda}) = 0$, which is an easy check to see if the algorithm works. The scores are used to estimate the information matrix, which is defined as

$$\tilde{\mathcal{I}}_1 = \frac{1}{T} \sum_{t=1}^{T} [h_t(\lambda)][h_t(\lambda)]' \quad . \tag{31}$$

The standard errors for the parameters are retrieved by

$$\text{std}(\lambda) = \text{diag}(\sqrt{\frac{1}{T} \tilde{\mathcal{I}}_1^{-1}}) \quad . \tag{32}$$

B.6 Definitions and matrix constructions

Variable	Definition	Size
T	Number of time steps	Scalar
M	Number of regimes	Scalar
l	Number of lags	Scalar
K	Number of indicators	Scalar
$\hat{T}_m$	$\mathrm{tr}(\hat{\Xi}_m)$	Scalar

(a) Scalars

Variable	Description	Construction	Size
y_t	Vector of obs. for time t	$(y_{1,t} \quad ... \quad y_{k,t})$	$(1 \times K)$
$\mathbf{y}$	Vector of all data	$(y'_1 \quad ... \quad y'_T)'$	$(T \cdot K \times 1)$
x_t	t'th row of $\bar{\mathbf{X}}$	$(y_{1,t} \quad ... \quad y_{k,t})$	$(1 \times K)$
ζ	Vector of probabilities of starting in state	$(\Pr[s_1 = 0] \quad ... \quad \Pr[s_1 = M])'$	$(1 \times M)$
$\hat{\xi}_{m\|T}$	Smoothed probs of being in state n at time t	$(\Pr[s_1 = m] \quad ... \quad \Pr[s_T = m])'$	$(T \times 1)$
$\boldsymbol{\nu}_m$	vector intercepts for regime m	$(\nu_{1,m} \quad ... \quad \nu_{k,m})'$	$(K \times 1)$

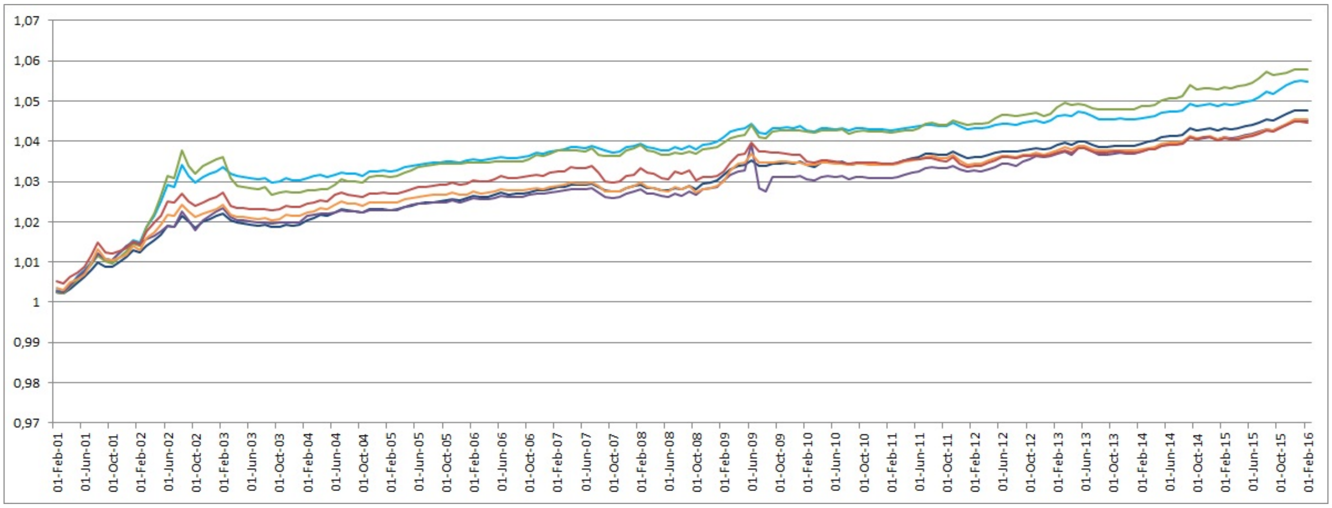
(b) Vectors

Variable	Description	Construction	Size
Σ_m	Covariance matrix of regime m		$(K \times K)$
$\Phi_{m,l}$	Autoreg. parameters for lag l and regime m		$(K \times K)$
Y	Matrix of input data	$(y_1 \quad ... \quad y_K)$	$(T \times K)$
Y_{-j}	Matrix of input data for lag j	$(y_{1-j} \quad ... \quad y_{T-j})'$	$(T \times K)$
$\bar{\mathbf{X}}$	Matrix of ones and lagged data for all lags	$(\mathbf{1}_T \quad \mathrm{Y}_{-1} \quad ... \quad \mathrm{Y}_{-l})$	$(T \times K \cdot l)$
$\mathbf{P}$	Regime transition prob matrix		$(M \times M)$
B_m	Matrix of intercepts and autoreg. par.	$(\boldsymbol{\nu}_m \quad \Phi_{1,m} \quad ... \quad \Phi_{l,m})$	$(K \times (1 + K \cdot l))$
$\tilde{\mathbf{U}}_m$	Matrix of normal distributed error terms	$\mathbf{Y} - \bar{\mathbf{X}}\tilde{B}'_m$	$(T \times K)$
$\hat{\Xi}_m$	Matrix with prob of state m on diagonal	$\mathrm{diag}\ (\hat{\xi}_{m\|T})$	$(T \times T)$

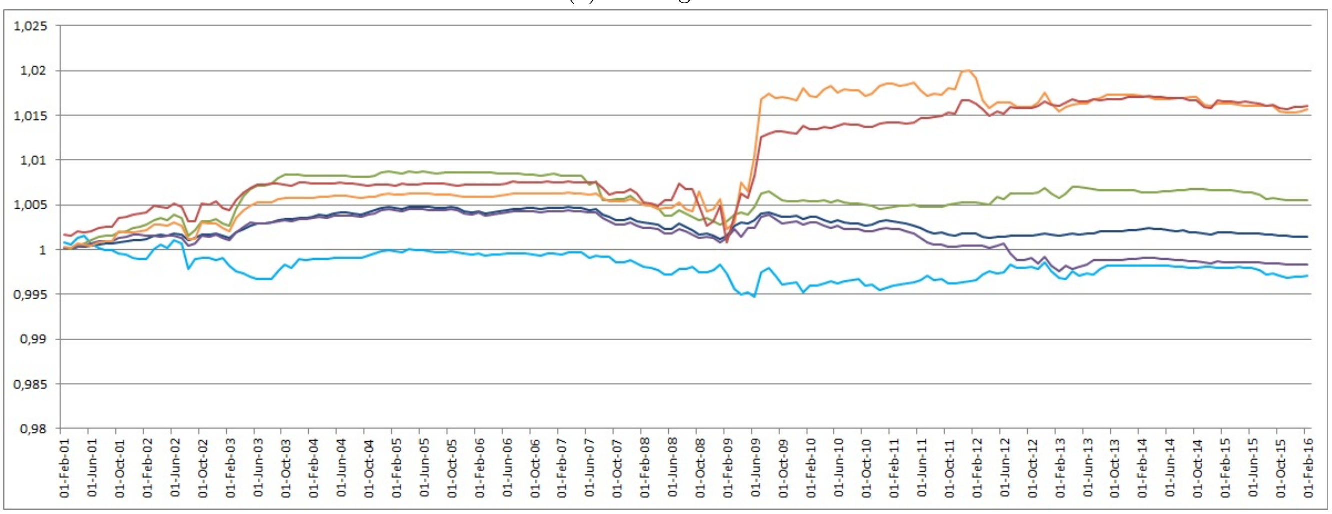
(c) Matrices

C Individual style results

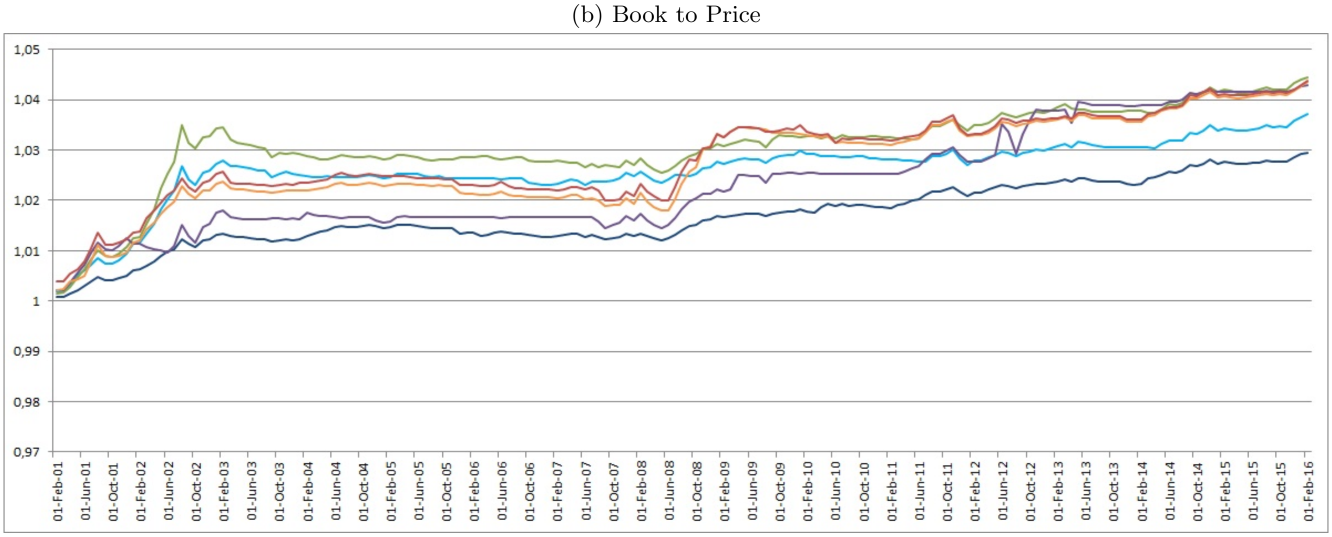
This Appendix presents some more detailed and elaborate results per style.



(a) Earnings Yield

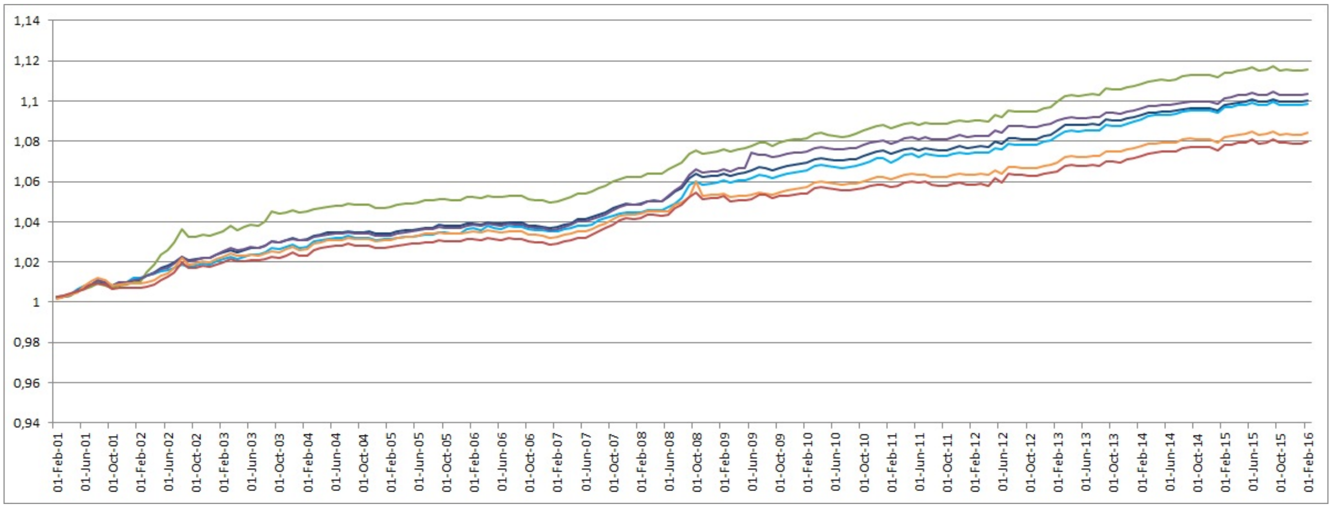


(b) Book to Price

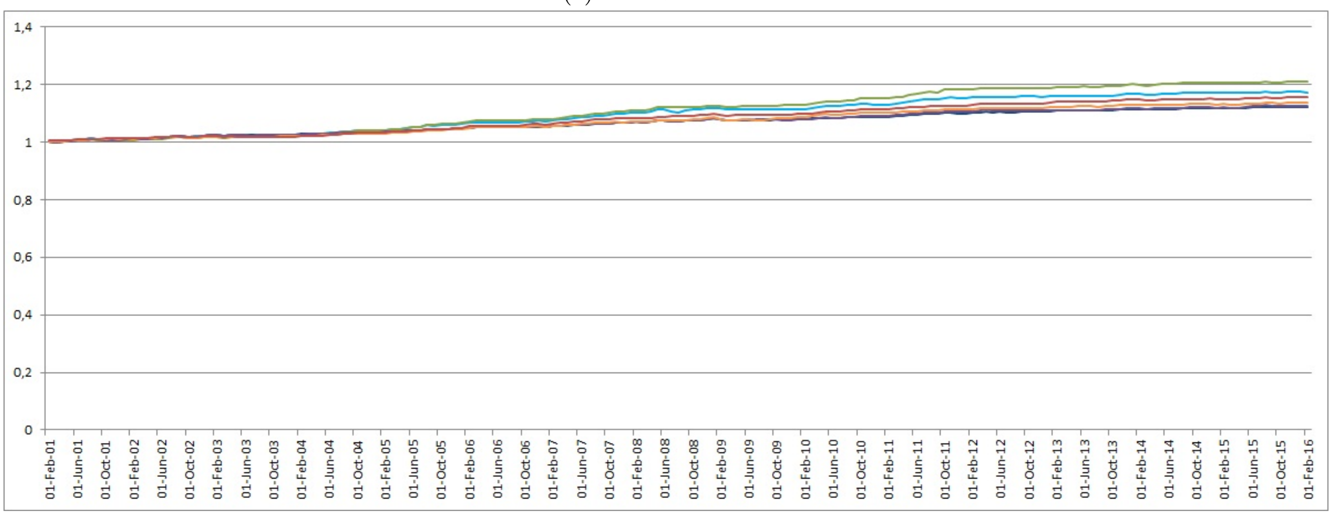


(c) Dividend Yield

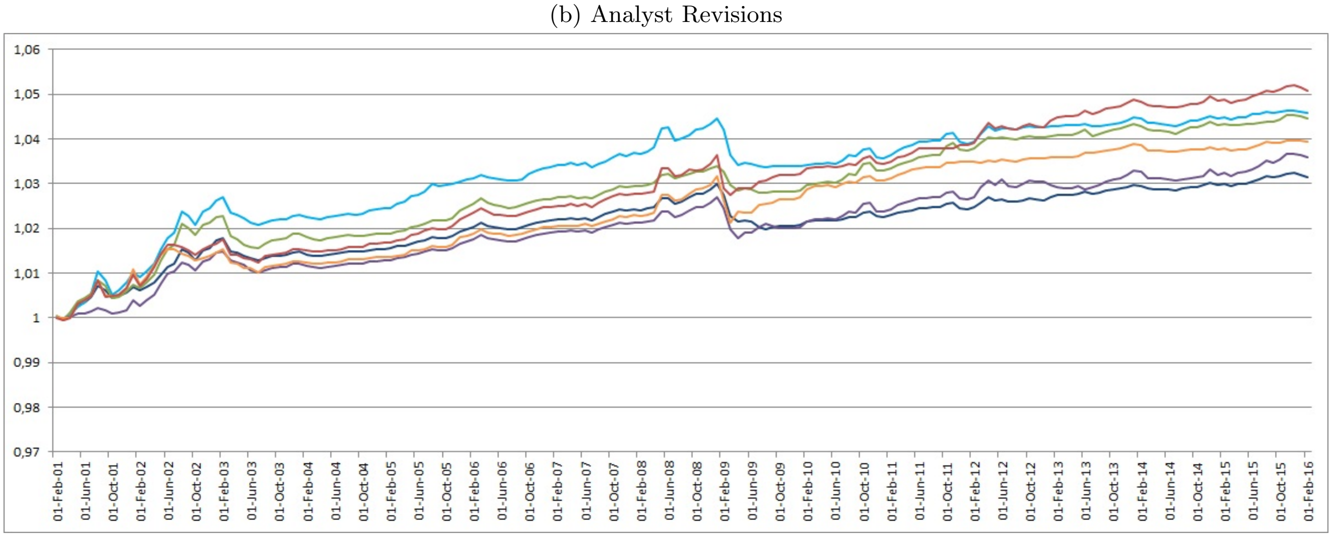
Figure 16: Individual style performance
Blue = Benchmark, Azure = BAML, Green = JPM, Purple = Nomura
Orange = VAR, Red = MS-VAR



(a) Free Cash Flow

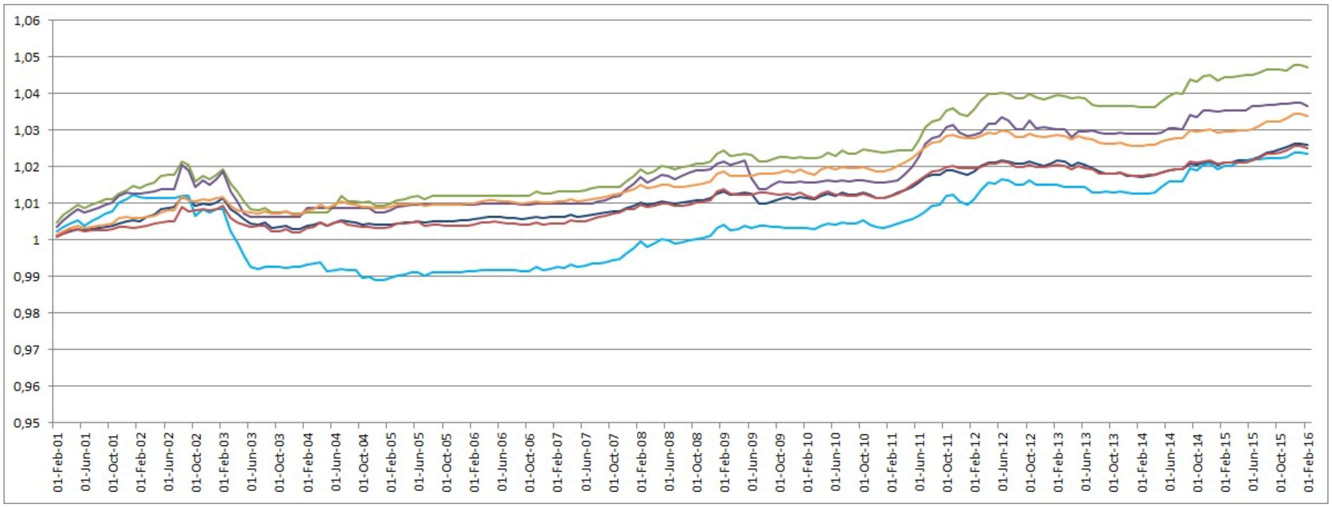


(b) Analyst Revisions

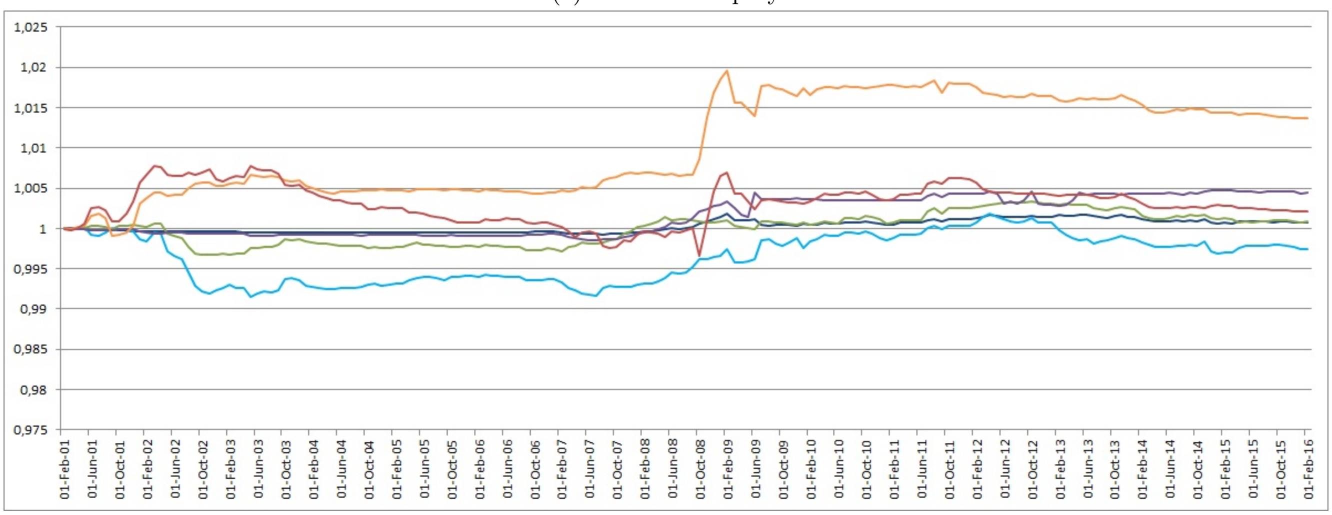


(c) Price Momentum

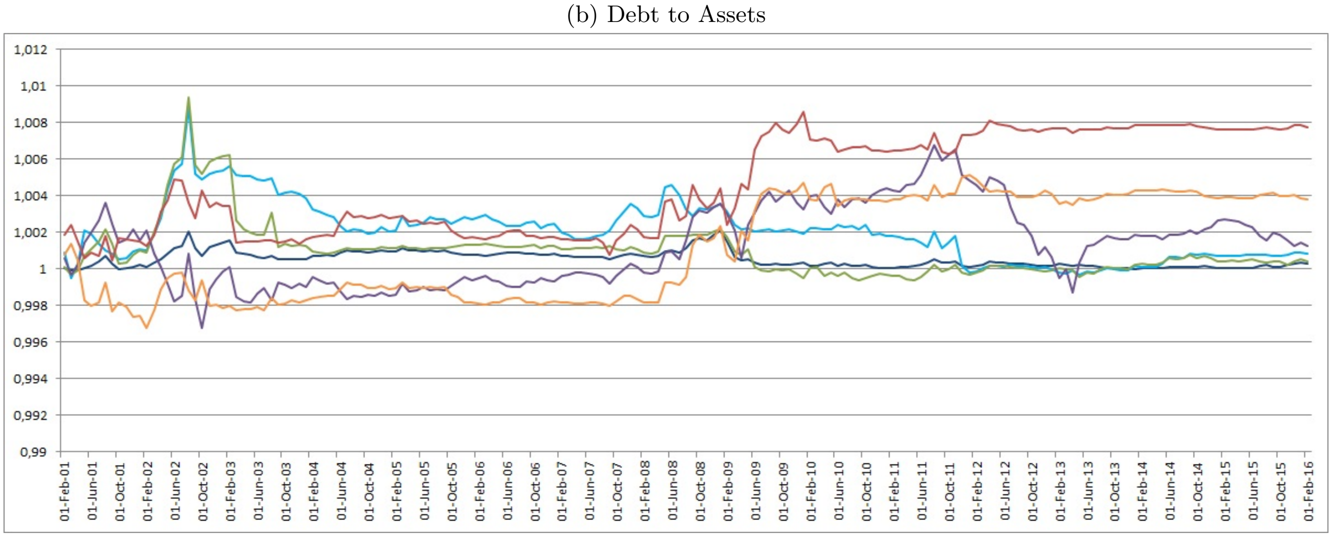
Figure 17: Individual style performance (cont.)
Blue = Benchmark, Azure = BAML, Green = JPM, Purple = Nomura
Orange = VAR, Red = MS-VAR



(a) Return on Equity

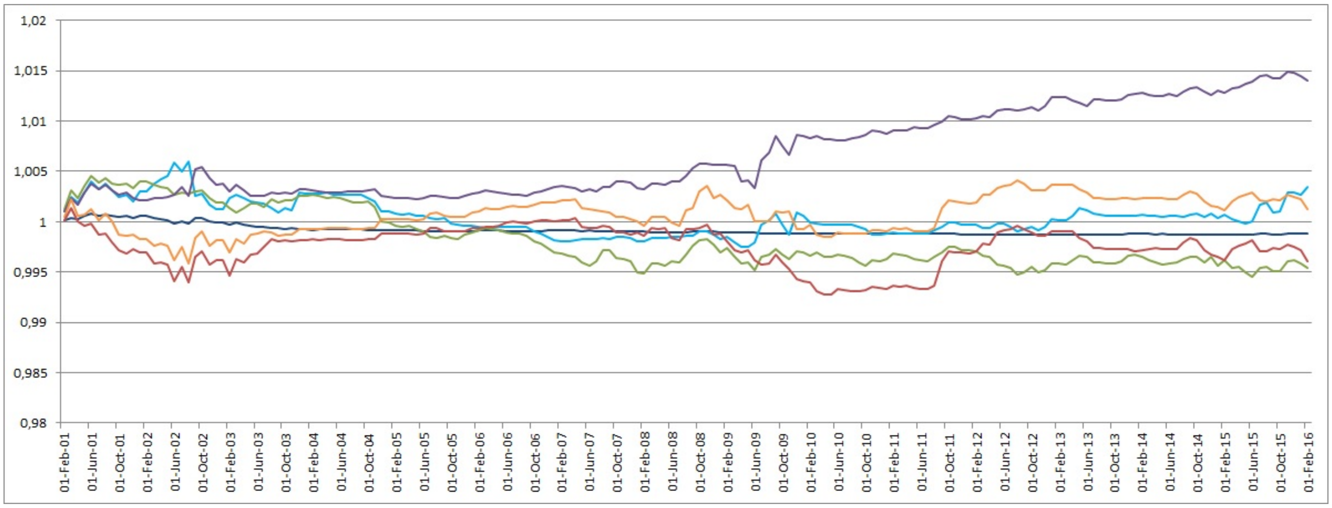


(b) Debt to Assets



(c) Market Beta

Figure 18: Individual style performance (cont.)
Blue = Benchmark, Azure = BAML, Green = JPM, Purple = Nomura
Orange = VAR, Red = MS-VAR



(a) Market Cap

Figure 19: Individual style performance (cont.)
Blue = Benchmark, Azure = BAML, Green = JPM, Purple = Nomura
Orange = VAR, Red = MS-VAR

	Means	EY	BP	DY	FCF	Anrev	PM	ROE	D/A	Beta	Size
	Unconditional	0,878	0,175	0,682	0,794	0,922	1,123	0,541	0,073	0,251	0,089
BAML	Downt	1,126	-0,123	0,971	0,737	1,106	1,010	0,928	0,216	1,255	-0,350
	Recess	1,334	-0,495	1,540	1,222	1,109	2,131	1,078	0,274	1,635	-0,411
	Recov	0,811	1,396	0,399	0,401	0,297	0,124	-0,030	-0,420	-1,478	0,784
	Expan	0,267	0,021	-0,235	0,827	1,179	1,303	0,162	0,203	-0,554	0,332
JPM	Downt	0,851	-0,105	0,790	0,656	1,196	0,936	0,799	0,141	0,833	-0,234
	Recess	1,632	-0,625	1,752	1,222	1,115	2,018	1,405	0,317	1,998	-1,050
	Recov	1,007	1,205	0,713	0,764	0,331	-0,076	0,263	-0,220	-0,971	0,605
	Expan	0,115	0,397	-0,503	0,584	0,989	1,532	-0,290	0,028	-1,029	1,012
Nomura	Downt	1,362	-0,136	1,367	0,964	0,892	1,605	0,979	0,158	1,420	-0,208
	Recess	0,810	1,925	0,857	0,662	0,290	-1,703	-0,350	0,088	-2,656	0,593
	Recov	-0,019	1,142	0,002	0,791	0,441	0,250	-0,610	-0,394	-0,307	1,024
	Expan	0,747	-0,117	0,331	0,705	1,149	1,472	0,635	0,107	0,096	0,013

(a) Mean returns per month per regime indicated by different brokers

	Variance	EY	BP	DY	FCF	Anrev	PM	ROE	D/A	Beta	Size
	Unconditional	5,094	9,036	5,762	2,272	3,173	15,937	3,970	2,120	32,063	6,543
BAML	Downt	5,813	6,830	5,962	2,320	1,575	5,245	3,153	1,738	19,767	4,910
	Recess	6,848	10,334	6,885	2,926	5,294	20,263	3,586	1,806	52,626	6,439
	Recov	4,002	11,215	3,395	2,232	3,404	24,375	5,002	2,553	32,989	6,637
	Expan	3,241	6,342	4,993	1,401	2,120	13,181	3,395	2,191	18,660	7,450
JPM	Downt	3,891	6,122	5,007	1,696	1,833	8,582	2,836	1,868	12,555	4,600
	Recess	8,202	10,334	7,581	3,588	4,155	13,873	2,489	1,967	48,659	6,620
	Recov	4,998	12,248	5,024	1,680	4,563	31,241	4,622	1,755	47,518	5,353
	Expan	2,527	6,820	2,983	1,925	2,169	11,276	4,464	2,738	18,650	7,133
Nomura	Downt	7,688	9,176	7,828	2,996	3,949	15,230	3,194	1,829	43,872	7,155
	Recess	4,879	21,683	3,573	1,663	5,343	44,764	5,618	3,190	61,113	5,631
	Recov	3,153	9,332	2,039	2,992	2,982	11,578	6,776	3,388	16,769	7,037
	Expan	3,462	5,792	4,981	1,725	2,146	10,380	3,102	1,825	19,678	5,918

(b) Variance per regime indicated by different brokers

	Sharpe ratios	EY	BP	DY	FCF	Anrev	PM	ROE	D/A	Beta	Size
	Unconditional	0,034	0,002	0,021	0,154	0,092	0,004	0,034	0,016	0,000	0,002
BAML	Downt	0,033	-0,003	0,027	0,137	0,446	0,037	0,093	0,072	0,003	-0,014
	Recess	0,028	-0,005	0,032	0,143	0,040	0,005	0,084	0,084	0,001	-0,010
	Recov	0,051	0,011	0,035	0,080	0,026	0,000	-0,001	-0,064	-0,001	0,018
	Expan	0,025	0,001	-0,009	0,421	0,262	0,007	0,014	0,042	-0,002	0,006
JPM	Downt	0,056	-0,003	0,032	0,228	0,356	0,013	0,099	0,040	0,005	-0,011
	Recess	0,024	-0,006	0,030	0,095	0,065	0,010	0,227	0,082	0,001	-0,024
	Recov	0,040	0,008	0,028	0,271	0,016	0,000	0,012	-0,071	0,000	0,021
	Expan	0,018	0,009	-0,057	0,158	0,210	0,012	-0,015	0,004	-0,003	0,020
Nomura	Downt	0,023	-0,002	0,022	0,107	0,057	0,007	0,096	0,047	0,001	-0,004
	Recess	0,034	0,004	0,067	0,239	0,010	-0,001	-0,011	0,009	-0,001	0,019
	Recov	-0,002	0,013	0,001	0,088	0,050	0,002	-0,013	-0,034	-0,001	0,021
	Expan	0,062	-0,003	0,013	0,237	0,249	0,014	0,066	0,032	0,000	0,000

(c) Sharpe ratios per regime indicated by different brokers

Figure 20: Performance of different styles in the different regimes as indicated by the broker models. Also the unconditional performance is given. These number are without any weight involvement.