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On the trails of Dragon Kings -

Predicting the highly improbable

Yield Curve as Recession Indicator in the framework of Machine Learning

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Abstract

This paper studies the infromation content of the yield curve as recession indicator in the Eurozone. This paper employs a dataset extending from 1970 to 2017 to create an aggregated syntheic yield curve for 3-month interest rates, 10-year interest rates and rate of GDP growth. This paper is the first to utilise Support Vector Machine for forecasting of recessions in the Eurozone.

The forecasting accuracy is tested in an out-of sample test. The model using only German term-spread proved to be the most accurate. Nevertheless, this model raised two false alarms between 2013 and 2016. Therefore, the findings of this paper are inline with previous emperical investigation indicating diminished information content of the yield curve.

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I. Introduction

Economic forecasts models are based on the complexity theory resembling those for weather forecast with a variety of variables of which some are unknown (Sornette, 2003). Therefore, economic forecasts and the whole forecasting field is received with scepticism, placing less trust into an economic forecast than into next week weather forecast. As John Kenneth a Canadian-born economist puts it "The only function of economic forecasting is to make astrology look respectable." In fact, in his book Nassim Taleb describes recessions as rare events or "black swans" meaning, being unpredictable. He argues that instead of trying to forecast them, we should adjust to their existence (Taleb, 2010). With this said, there would be no meaning for another paper on recession forecasting. However, in his paper Sornette (2010) developes an opposite concept of "dragon-kings" theory, those are meaningfull outliers revealing meachnisms of self-organization, hence the thesis name. Sornette argues that most crises are endogeneous and can be diagnosed in advance (ex-ante). The financial crisis observatory (FCO) lead by Sornette earned him a nickname of "dragon-king hunter" because of their succesful ex-ante prediction of several bubbles within different economies followed by a market correction. Nevertheless, majority of forecasts rely on either complex models with variety of variables or on linear models which are deemed as unsuitable for proper representation of the dynamic economic responses (Galvão, 2006). Despite the complexity and poor track record, economic forecast play a vital role for policy makers such as central banks, but also for pension funds, passive mutual funds and insurance companies.

Over the decades the slope of the yield curve spread between ten-year Treasury bond rate and the three-month interbank-rate persisted as best recession predictor (Estrella & Hardouvelis, 1991; Hamilton & Kim, 2001; Berk, 1998). According to Estrella and Mishkin (1997) despite the influence of the central banks over the short-term interest rates, the long-run rates are determined by numerous factors, including the market expectations. Therefore, the predictive power behind it could be useful for policy makers making decision about the short-term rates to influence the economic activity. However, the absolute predictive power of models is not the crucial part of forecasting but rather the range, relationships and direction it provides to the decision maker.

The purpose of this paper is to replicate the findings by Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014) on the European market using an aggregated European yield curve.

In the following section the paper describes the relationship between the slope of the yield curve and economic activity. Next, the paper summarizes relevant literature and previous findings related to yield curve forecasting ability. Third section, provides an overview of SVM approach and the assumptions made for the model. Fourth section, presents the methods for data selection, gathering and cleaning. In the fifth section, the paper provides an analysis and results for the model. Sixth section, provides an interpretation of the findings followed by economic implications and conclusion.

II. The Relationship between the Slope of the Yield Curve and Economic Activity

A yield curve represents the relationship between yields of bonds with varying maturities and their remaining time to maturity issued by a single entity (ECB, 2018). A yield curve is described as the term structure of interest rates. It is also used as benchmark for other debt securities in the market.

Thus far there is no single unifying theory behind the relationship between yield curve and economic activity. There are at least two main reasons explaining the relationship between yield curve and its information content on future economic activity. The relationship in free economies is generally positive meaning, a positive term-spread between long-term rates and short-term interest rates results in an upward sloping curve and vice versa. The term-spread is based on long-term rates usually on 10-year government bonds and short-term rates either 3-month government bills or 90-day interbank rate such as LIBOR. Previously all recessions were preceded by a flat- or inverse yield curve (see Figure 1, page 13).

The first reason stems from a combination of the Fisher equation (1) and the expectations hypothesis (Berk J. , 2000). According to expectation hypothesis long-term interest rate should equal the sum of current and expected future short-term interest rates plus a term premium thus, a portfolio of weighted average of expected future short-term rates. The hypothesis builds on the Fischer decomposition of nominal yields (Bernadell, Coche, & Nyholm, 2015). As shown in equation (1) the term-spread (left hand side) consists of expected real interest rate and expected market inflation, hence the expectation hypothesis (Berk J. , 2000). In his paper, Mishkin (1990) finds that the yield curve predicts long-term inflation offering support to the expectation hypothesis with similar results obtained by (Estella & Hardouvelis, 1991). The term premium is also responsible for the upward sloping curve during an expected economic growth (Berk J. , 2000). The expected inflation increases and so does the premium to compensate the investors for holding long-term securities. The opposite holds true during expected recession, resulting in a flattening or inverse yield curve. Therefore, central banks use this behaviour as an instrument for monetary policy by adjusting the short-term rates.

The second reason is based on the intertemporal consumption theory where the term-spread is affected by investors demand in anticipation of either a growth or recession. Whereas, investor prefer stable income during growth and low income during recession. Subsequently they sell short-term bills during recession while buying long-term bonds (Moneta, 2005). The increased demand for long-term bonds decreases the corresponding yield leading to flattening of the yield curve. The support for this hypothesis stems from a paper by (Harvey, 1988) successfully forecasting both consumption and output growth based on the slope of the yield curve. Lastly, several studies find that monetary policies alone cannot explain all the observed relationships thus, indicating that yield curve is determined by numerous factors, including the market expectations (Estella & Hardouvelis, 1991; Estralla & Mishking, 1998; Wheelock & Wohar, 2009).

$$R(n,t) - R(1,t) = E_t[r(n,t) - r(1,t)] + E_t[\pi(n,t) - \pi(1,t)] \quad (1)$$

$\mathrm{r(n,t)}$, *is the average real interest rate over the current and next n-1 periods,* $\pi(\mathrm{n,t})$ *is the average inflation rate over the next n periods with* $\mathrm{r(1,t)}$ *and* $\pi(1,\mathrm{t})$*being spot rates.*

III. Literature Review

Over the last three decades vast amount of studies provided evidences on the information content and predictive power of the term-spread for real output, growth and recession. This paper focuses on the studies forecasting recessions in EU rather than output growth.

In their paper Estella and Hardouvelis (1991) laid the foundation for the coming studies by forecasting recession for US with the help of the term-spread using a probit model. Estella and Hardouvelis (1991) found evidence for significant forecasting ability of the term-spread compared to other prominent indicators. This is confirmed by Estralla and Mishkin (1998) who in addition find that inclusion of stock index as explanatory variable imrproves the forecating ability. Following suit on US studies, Estrella and Mishkin (1997) perform similar analysis on European economies (France, Germany, Italy and United Kingdom) and provide empirical evidence for the use of term-spread. Furthermore, they show that term-spread has information regarding future growth and inflation. However, Estrella and Mishkin (1997) note that monetary policy is unlikely to be the sole determent of yield curve thus, should be used as " a useful check on the accuracy of a macroeconomic forecast derived using a broad set of information.". In contrast, European yield curve according to Hardouvelis (1994) and Bernard & Gerlach (1996) has a limited information content. In his paper Berk (2000) finds a limited practical usefulness of the European yield curve. As Berk (2000) argues, the main implication is due to different information content of the different EU country's yields. However, over the following years the doubt in information content and predictive power of the yield curve was disproved and further relationships confirmed. In a study performed by Gogas, Chionis, and Pragkidis (2009), they confirm the predictive power of yield curve for EU. Furthermore, they establish that inclusion of unemployment rate is not statistically significant, but the inclusion of three major EU stock price indexes improved the model (Gogas, Chionis, & Pragkidis, 2009). Among the EU focused papers, the paper by Moneta (2005) stands out as most detailed with regard to data. Moneta for the first time constructs a full historical aggregated database on: Austria, France, Germany, Italy, Netherlands and seven other countries from 1970 on. Among the ten tested term-spreads, Moneta establishes that the 10-year minus 3-month, lagged at 4 quarters is the best predictor of recession up to 4 quarters ahead (Moneta, 2005). Furthermore, Moneta extensively tests the robustness of these predictions by comparing term-spread to OECD Composite Leading Indicator (CLI) for EU area and through adoption of three different recessioin defintions. The OECD CLI proves to be a poor predictor, but adoption of different recession definition improves significantly the model. Moreover, Moneta shows that the results are mutually consistent meaning, that the model based solely on German term-spread has a rather siginificant predictive power for other EU countries because of the large German GDP weight. This finding is also supported by Gerlach and Bernard (1998) who find that German and U.S. term-spread are frequently significant in the regressions for other countries. In contrast to previously mentioned papers, the paper by Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014) uses the Support Vector Machine (SVM), a machine learning technique instead of a probit model. This was the first empirical investigation on the relation between yield curve and economic activity using an SVM classifier. The only similarities between the papers, is that variable being predicted is binary, meaning it takes only two possible values either it is a recession or an expansion. In their paper Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014) adopt a recession definition described by output gaps between long-run

GDP trend and real GDP. They achieve an overall forecasting accuracy of 66.7% and 100% accuracy in forecasting recessions. The overall accuracy is affected by false positive, meaning model forecasted a recession when there was none. Bottom line, the SVM model outperforms the standard logit and probit models using only term-spread as explanatory variable while relying on a shorter time frame (1976 to 2011).

Just like Moneta's paper, this paper uses aggregated yield curve (synthetic yield) based on yields of seven EU countries. Further, this paper adapts methodology developed by Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014) using the Support Vector Machine classifier (SVM). The main objective of this paper is to replicate findings by Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014) on the European market using an aggregated European yield curve. The secondary goal of this paper is to create a forecasting model that is easy to use with a freely available information for policy makers as well as institutional investors. The uniqueness of this paper's dataset makes it possible to test yield curve as recession indicator for EU. Furthermore, this paper will use recent monthly data (1970:1 to 2017:7) to asses their potential yield curve usefulness. In the following section SVM is described.

IV. Methodology

a. Model

Support vector machine (SVM) and probit model which is based on logistic regression (LR) are closely linked via the support vector classifier (SVC). Logistic regression is probabilistic using maximum likelihood to fit the model since p(X) in equation (2) can take values between 0 and 1 (see Figure 3). Maximum likelihood function tries to estimate $\hat{\beta}_0$ and $\hat{\beta}_1$ in equation (2) such that p(X) is either close to 1 during a recession and 0 otherwise (James, Witten, Hastie, & Tibshirani, 2013). Maximum likelihood (ML) function is an approach used to fit non-linear data, in fact least square approach used in linear regression is a special case of ML. Whereas, SVC is deterministic instead of assigning probability to each outcome it makes the right decision by assigning either 1 to recession and 0 otherwise. Both logistic regression and SVC use a separating hyperplane to classify the data (see Figure 4). However, SVC[1] tries to define a hyperplane while maximizing the margin the 'street' around the separating hyperplane (James, Witten, Hastie, & Tibshirani, 2013). Support vector classifier's decision rule is based only on a small subset of the observations (the support vectors) it means that it can effectively deal with outliers. Support vector machine is an extension of SVC coupled with a non-linear kernel[2] that involves inner products of the observation to project the hyperplane into higher-dimensional space, when data is not linearly-separable (see Figure 5). The method has two basic steps: the training step and the testing step. The dataset is split into training data and into test data usually 70% for former and 30% for the latter. The error tolerance parameter C and λ are investigated through a grid-search (Gogas, Papadimitriou, Matthaiou, & Chrysanthidou, 2014). Grid-search is a way to select the best model out of set of models with varying C and λ parameters on the grid hence, the grid-search. However, models are tools which are useless without valid and clean data.

$$p(X) = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}} \quad (2)$$

b. Data

To carry out the empirical analysis, this paper requires aggregated European historical time series on interest rates and growth rate of GDP. Data on GDP, GDP growth rate and short- and long-term yields is obtained on: Germany, Spain, France, United Kingdom, Ireland, Italy and

[1] $\underset{\beta_0,\beta_1,\ldots,\beta_p}{minimize}\left\{\sum_{i=1}^{n}\max[0,1-y_i f(x_i)]+\lambda\sum_{j=1}^{p}\beta_j^2\right\}$, where λ is a nonnegative tuning parameter. When λ is large the margin becomes softer resulting in a low-variance but high-bias.

[2] $K(x_i,x_{i'})=\exp\left(-\gamma\sum_{j=1}^{p}(x_{ij}-x_{i'j})^2\right)$, is the radial kernel which is used in this paper.

the Netherlands (EU7). In particular, 3-Month interbank and 10-Year government bonds are used for the yields, indicated as best recession predictors by Estrella & Mishkin (1997); Gogas, Papadimitriou, Matthaiou, & Chrysanthidou (2014); Moneta (2005). The data is retrieved from several sources and interpolated using linear method (see Appendix B for details). The GDP growth rate is seasonally adjusted by FRED using the ARIMA[3] model (Anderson, Rasche, & Loesel, 2003) (see Table 7). The seasonal adjustment allows potential short-term cyclical patterns to be identified to produce smooth non-linear data centered around its long-lasting trend, thus isolating cyclical component of GDP growth rate (Gogas, Chionis, & Pragkidis, 2009). The paper ends up with a monthly data from 1970 for all three data points. For the data aggregation the paper uses relative GDP weight[4] of the country for the given period since 1970 at current US$ prices (see Table 9). Thus, the paper obtains one (WAV)[5] aggregated short-term yield, long-term yield and GDP growth rate from all EU7 countries. From WAV yield rates a synthetic spread is constracted, interestingly there is no performance difference of the model using term-spread constracted from the WAV long-term minus short-term yields and term-spread constructed from the term-spreads of EU7 countries using GDP weights.

The paper focuses on the cyclical component of GDP growth rate, thus a binary (dummy) variable is created with a value of 1 during recession and 0 during an expansion. For this purpose, the paper uses OECD based Recession Indicators for Euro Area on a monthly basis, obtained from OECD site (OECD, 2017) (see Table 8). OECD recession definition is based upon simplified algorithm from Bry and Boschan (1971) which utilizes “growth-cycle” approach. The growth-cycle approach identifies the turning points which are measured and identified as deviation from the long-term GDP trend. Table 1 provides a detailed overview of

[3] An autoregressive integrated moving average (ARIMA), which is a part of software package X-12-ARIMA a seasonal adjustment software developed and supported by the United States Census Bureau
[4] Beyer, Doornik and Henfry (2001) propose to aggregate weighted within-country growth rates to obtain euro-zone growth rates
[5] WAV as weighted average

the term-spreads including the WAV synthetic spread. A clear pattern can be seen (see Figure 1) that each crisis was preceeded by a flat term-spread. Further tables with descriptive statistics for 3-month and 10-year interest rates are provided in appendix A Table 3 and Table 4. Moreover, figures for German 3-month and 10-year interest are provided in appendix A (see Figure 6) along with similar figures for WAV yield curve (see Figure).

Table 1: Descriptive statistics of term-spreads including the synthetic spread (S_WAV)

Spreads	S_DEU	S_ESP	S_FRA	S_GBR	S_IRL	S_ITA	S_NLD	S_WAV
count	571	571	571	571	571	571	571	571
mean	0.99	0.47	1.10	1.07	2.29	-0.38	1.31	0.79
std	1.52	2.23	1.31	2.53	3.06	3.42	1.23	1.21
min	-4.79	-12.02	-4.29	-4.57	-29.62	-10.68	-1.46	-2.29
25%	0.20	-0.77	0.37	-0.57	0.61	-1.97	0.47	-0.05
50%	1.20	0.50	1.35	0.95	1.83	0.45	1.30	0.89
75%	2.07	1.79	2.06	2.16	4.06	1.79	2.18	1.70
max	4.62	6.30	3.75	10.14	10.21	5.58	4.36	3.05

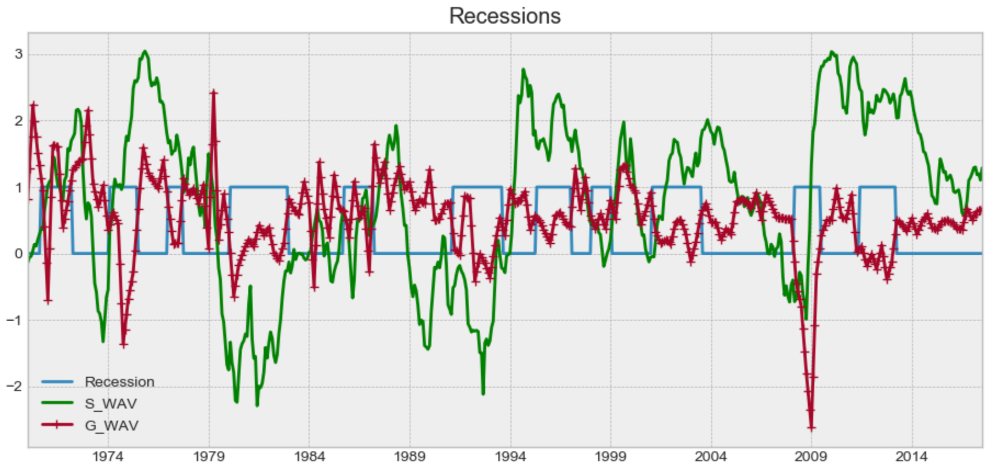

Figure 1: Recession period according to OECD along with synthethic term-sprad and synthethic GDP growth

V. Analysis

Following the steps outlined earlier at the end of model section, the data was split into two periods for in-sample training and out-of-sample test to validate the model. The first in-sample period extends from 1970:1 to 2005:12 during which 11 recessions occur. In-sample training calculates the parameters for hyperplane while maximising the margin. While in-sample-training is trained to forecast recession using the whole period. By contrast out-of-sample (2006:1 to 2017:7) test is using only information available to market participants at the time of the forecast. The parameters obtained in the in-sample training are then validated in out-of-sample test and enhanced via grid search if necessary. Furthermore, an in-sample training is prone to "overfitting" through addition of new explanatory variables, while out-of-sample test validates the true ability of the model. The analysis yields six models using different term-spreads (see Table 2). Inclusion of term-spreads from Ireland, Spain and the Netherlands decrease the forecasting ability of the model, hence they are not included in further analysis.

Another issue occurs when analysing the goodness of fit. In the classical regression, R^2 is used as measure of explanatory power of the model. As observed by Estella and Hardouvelis (1991) standard R^2 would yield values close to 1^{22}. In their paper they adapt a pseudo-R^2 which is used throughout most papers using the probit model. In constrast SVM is deterministic in nature thus, a confusion matrix can be used indicating the number of false negatives and false positives (see Table 5). Next, numbers obtained in the confusion matrix are used for calculation of F_1-score[6] which is interpreted as a weighted average of the precision and recall, where an F_1-score reaches its best value at 1 and worst score at 0.

Out of six models, model using German term-spread (Germany Adj.) proves as the fittest which is in line with findings by Moneta (2005) (see Table 2). Moneta indicated that Germany is the most important euro area country (in terms of GDP), having therefore the largest weight in the aggregation of WAV term-spread. The quality of the forecast for the German model is evaluated in the Figure 2. The model correctly identifies 2007-2009 and 2011-2013 recessions, preceded by flattening or inverse term-spread. In contrast, after 2013 the model raises two false alarms because of the flattening term-spread. The error tolerance parameters C and λ coefficients are

[6] F_1 = 2 * (precision * recall) / (precision + recall)
Precision = true positives / (true positives + false positives)
Recall = true positives / (false negatives + true positives)

either left at default (1.0 and 0.01 respectively) or reported as obtained via grid search. Small C and λ lead to higher bias resulting in a bias-variance trade-off which results in over sensitive forecasting and higher false positive number. Evaluating the overall performance of this model it can be stated that it has significant power to forecast upcoming recessions, albeit with dwindling information content because of artificially low interest rates.

Table 2: Measures of fit for models using different recession predictors

Predictor: Spread 10Y-3M	Precision	Recall	F1-score	N-samples	C	gamma
WAV	0.86	0.71	0.72	139	1.0	0.01
Germany	0.82	0.78	0.79	139	1.0	0.01
Germany Adj.	0.85	0.85	**0.85**	139	9.0	0.01
DEU, FRA	0.86	0.75	0.76	139	1.0	0.01
DEU, FRA, ITA	0.71	0.71	0.71	139	1.0	0.01
DEU, GBR	0.81	0.74	0.75	139	100.0	0.0001

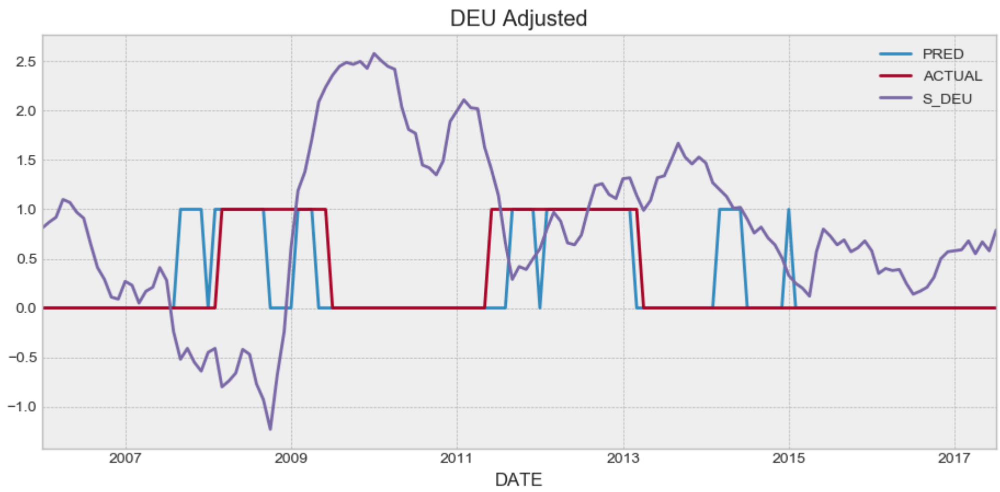

Figure 2: Visaul representatin of forecasting ability of the model using only (German Adj.) term-spread

VI. Interpretation

The results of the empirical investigation are in line with findings by Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014). They achieve similar results for the U.S. market using U.S. term-spread, and in similar fashion their model also indicates false positives signals for six quarters. As shown in Figure 2 the model corecctly forecasted all recessions up until to 2013 and in 2009 recession, the model raised an alarm before the start of crisis. Therefore, according to theory and previous findings the model performed well and based on previous data, there were supposed to be at least two more recessions. However, the successive flattening of the yield curve from 2013 was not accompanied by further recessions. In part, this can be explained by interest rates kept artificially low or in negative range by the ECB. Since price stability is one of the main objectives of ECB's monetary policy. In may 2010 ECB began buying government and private debt securities alevating the pressure from the GIPS states thus, lowering the yield on coresponding bonds. The recession period of 2011-2013 (European debt crisis) was caused by the threat of Greece's default with successive defaulting in 2012 and near default of Cyprus. Further credit infusion of €489bn into European banking system followed in December 2011 at low rates (ECB, 2011). Making sure that banks can pay off their maturing debt. From 2010 until 2015 ECB cut the prime interest rate to 0.15% while setting the deposit rate to -0.10% (NY Times, 2014). With interest rates low or negative conventional interest rate adjustments as a tool was exhausted. Thus, in 2015 ECB introduced a qunatitive easing program an expanded asset purchase programme aiming at keeping the inflation rate at a target rate of 2%, the interest rates low and to provide additional liquidity (ECB, 2015). Thus, ECB learned their lesson and kept the inflation and interest rates succesffuly at low rates. Consequently, the model forecasted a recession, raising false alarm because the yield curve became ECB's objective, keeping the interest rates artificially low rather than being determined by the market expectations.

VII. Economic Implications

Under current economic policies yield curve is less informative as recession indicator. This is inline with findings by Chinn and Kucko (2010); Schrimpf and Wang (2010) indicating a diminished forecating ability. Thus policy makers cannot rely on the yield curve as sole indicator comparable to a broken compass in an economic Bermuda triangle. Therefore, models should rely on other metrics rather than yield curve, in best case multiple metrics should be used jointly.

Under current economic conditions investors such as pension funds should wait and see how ECB will react. With long-end of the yield curve low, pension funds and insurance companies are the biggest losers forced to spend more to get the same annual return (Kao & Authers, 2016). However, from 2017 both UK and U.S. started slowly to increase their interest rates expecting economic growth thus, also increased inflation in the future. This caused an exodus from long-term bonds previously used by investors as safe-heaven in anticipation of recession. However, according to industry experts the 35-year long bond bull market has come to an end (Wilson, 2017). With recent developments in interest rates and end of U.S. quantitative easing program, yield curve might rebound back indicating upcoming period of growth. Such developments would greatly benefit pension funds and insurance companies. This developments in U.S. would put ECB under pressure to follow suit thus, liberating the yield curve of artificial bondages. Hence, in theory yield curve would be re-established again as a recession indicator.

VIII. Limitations

The research is complicated by the fact that recessions are a rare event. This is further complicated by the availability of data especially within the Eurozone. Furthermore, next to lacking data, another issue arises in form of complicated data aggregation because of different currencies, monetary policies all resulting in varying information content of the yield curve. Therefore, future research should closely address the aggregation issues and consider additional explanatory variables. Moreover, future research should look more closely into the issue that the GDP is released with a delay and is subject to revision, trying to estimate the best lag. Additionally, a larger yield curve sample should be considered consisting of most EU countries to smooth out the German yield curve influence due to high GDP weight. Moreover, yield curve should be adjusted for quantitative easing influence e.g. by adjusting for ECB purchase of respective country bonds. Lastly, this paper adapts only one recession definition from OECD. As mentioned by Moneta (2005) varying recession definitions can lead to model improvements which should be addressed in the future.

IX. Conclusion

This paper is the second empirical investigation on the relationship between the yield curve and future economic activity using an SVM classifier. The main objective of this paper was to replicate the findings by Gogas, Papadimitriou, Matthaiou, and Chrysanthidou (2014) and the secondary goal of this paper was to create a forecasting model that is easy to use with freely available information for policy makers as well as institutional investors using yield curve as recession indicator. The empirical analysis suggests that the practical usefulness of the yield curve for predicting future recession in the euro area is limited. The paper focused on the term-spread between 10-year and 3-month interest rates. To achieve that, term-spreads were aggregated using GDP as weight from 1970 to 2017 on. Using this aggregated term-spread and other term-spreads six models were trained, which accuracy to forecast was tested in an out-of-sample test using SVM. The SVM model is deterministic using binary variables indicating recession as 1 and an expansion as 0. Furthermore, because data variables were not-linearly separable a kernel trick was used. Among six models, model using German term-spread as explanatory variable gives the best results a F_1-score of 0.85. However, the model raised two false alarms indicating issues with the robustness of the model. The issues, are in part explained by the model settings, but the main reason for false alarm is the flat yield curve. The EU yield curve is held artificially low by the ECB in effort to preserve price stability within the Eurozone. Therefore, as long as yield curve is artificially determined, the information content as such is non-existent since ECB’s action bear most information. Nevertheless, once the yield curve is free of large interventions the model can be used in conjunction with other tools as recession indicator empowering and supporting the policy makers in their decisions. However, the absolute predictive power of the model should not be used as policy directive, rather as a broad guideline. Lastly, machine learning is no wonder tool and depends on sound data same as other various forecasting tools.

"He who lives by the crystal ball soon learns to eat ground glass." — Edgar R. Fiedler (Italian economist)

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Appendix A

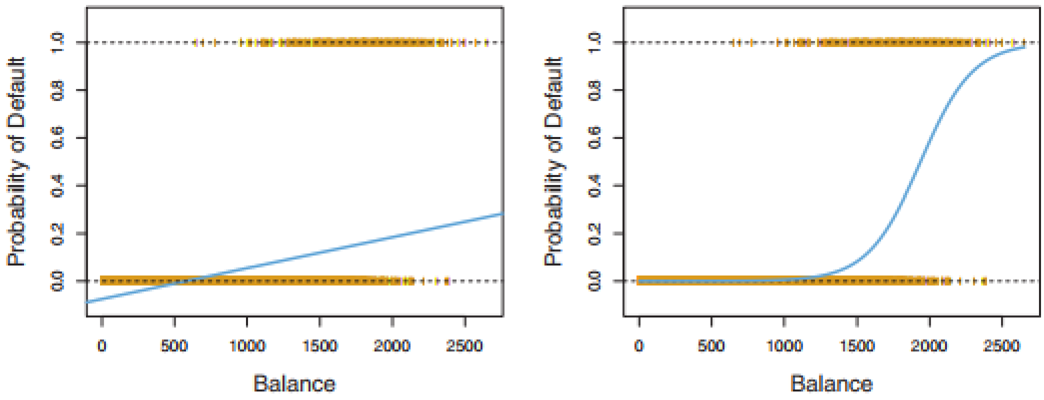

Figure 3: Left estimated probability using linear regression, some estimated probabilities are negative. Right: predicted probabilities using logistic regression, all probabilities are between 0 and 1.

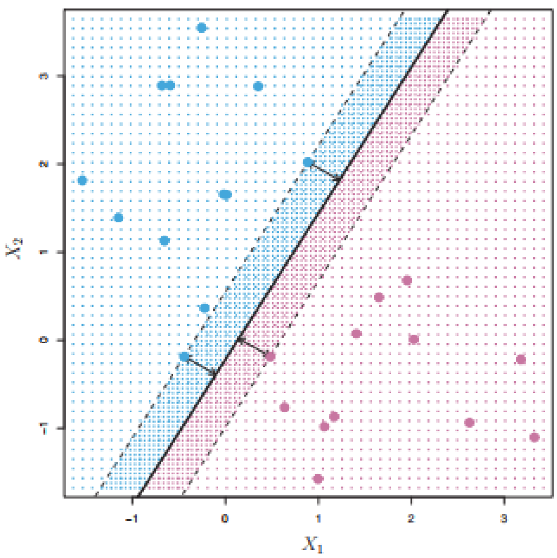

Figure 4:SVC classifier. There are two classes of bservations separated by the hyperplane, The margin is the distance from the solid line to either of the dashed lines. The three points on the dashed line are the support vectors (James, Witten, Hastie, & Tibshirani, 2013). No porbabilities, clear class separation.

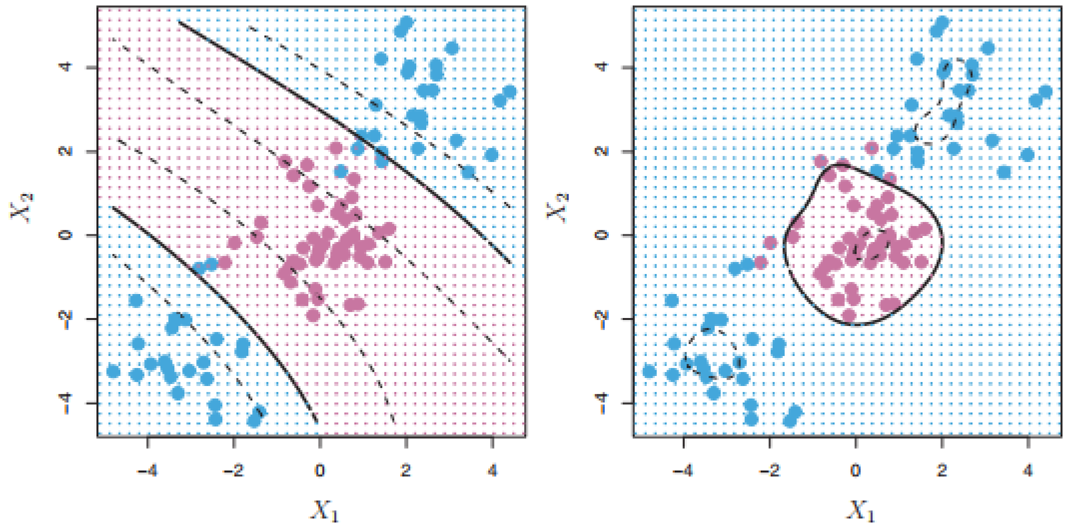

Figure 5: Left:an SVM with a polynomial kernel. Right: an SVM with a radial kernel which is used in the analysis. The radial kernel projects the hyperplane into higherdimension by taking the self-product of the explanatory variable.

Table 3: Descriptive statistics for long-term yields including syntheic yield (WAV)

Long	**10-Year DEU**	**10-Year ESP**	**10-Year FRA**	**10-Year GBR**	**10-Year IRL**	**10-Year ITA**	**10-Year NLD**	**10-Year WAV**
count	571	571	571	571	571	571	571	571
mean	5.79	8.72	7.32	7.84	8.51	7.39	6.05	7.03
std	2.65	4.62	3.99	3.91	4.46	3.46	2.73	3.22
min	-0.15	1.01	0.15	0.74	0.32	1.18	0.03	0.43
25%	3.97	4.45	4.05	4.62	4.69	4.54	4.03	4.20
50%	6.20	8.28	7.77	8.06	8.62	6.48	6.35	7.65
75%	8.00	12.59	10.12	10.88	11.96	10.45	8.21	9.63
max	10.80	18.11	17.32	16.34	19.16	14.42	12.30	13.43

Table 4: Descriptive statistics for song-term yields including syntheic yield (WAV)

Short	**3-Month DEU**	**3-Month ESP**	**3-Month FRA**	**3-Month GBR**	**3-Month IRL**	**3-Month ITA**	**3-Month NLD**	**3-Month WAV**
count	571	571	571	571	571	571	571	571
mean	4.79	8.25	6.21	6.77	6.22	7.77	4.74	6.24
std	3.24	6.09	4.27	4.24	4.37	5.69	2.91	3.94
min	-0.33	-0.33	-0.33	0.32	-0.33	-0.33	-0.33	-0.20
25%	2.70	2.70	2.70	4.55	2.70	2.70	2.70	3.16
50%	4.46	7.84	5.99	6.15	5.93	7.49	4.76	6.45
75%	6.64	13.35	9.57	9.87	9.72	11.51	6.80	9.49
max	14.57	26.12	18.92	18.11	40.00	20.51	10.56	15.45

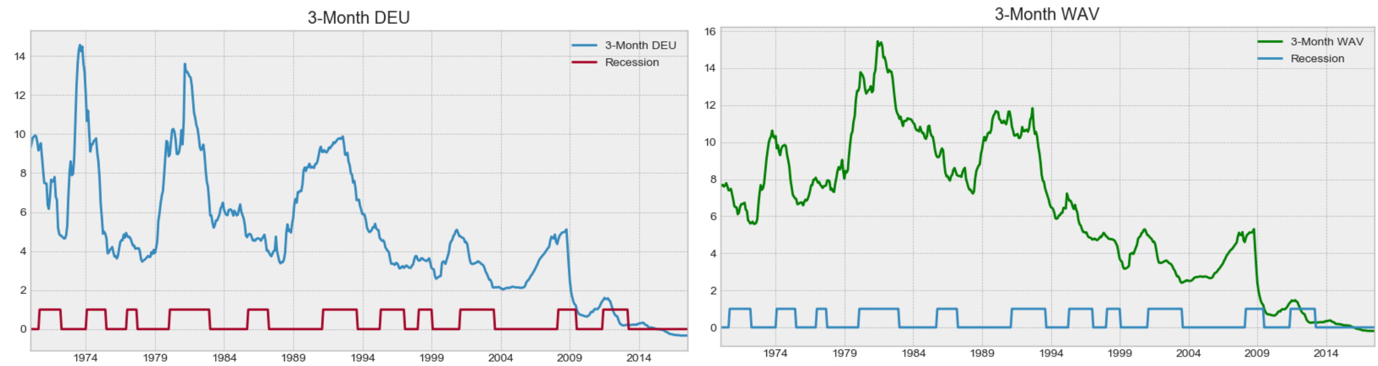

Figure 6: Visual representation of 3-Month German and synthetic yield development from 1970 to 2017

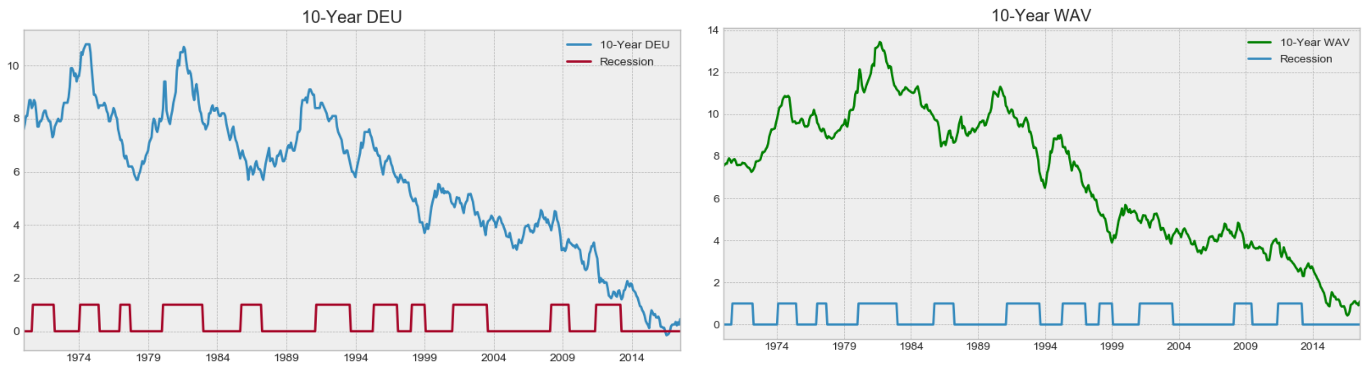

Figure 7: Visual representation of 10-Year German and synthetic yield development from 1970 to 2017

Table 5: Confusion matrix for all six models

WAV	Predicted: NO	Predicted: YES
Actual: NO	60	41
Actual: YES	0	38

DEU,FRA	Predicted: NO	Predicted: YES
Actual: NO	67	34
Actual: YES	1	37

German	Predicted: NO	Predicted: YES
Actual: NO	78	23
Actual: YES	7	31

DEU,FRA,ITA	Predicted: NO	Predicted: YES
Actual: NO	81	20
Actual: YES	20	18

German Adj.	Predicted: NO	Predicted: YES
Actual: NO	91	10
Actual: YES	11	27

DEU,GBR	Predicted: NO	Predicted: YES
Actual: NO	71	30
Actual: YES	6	32

Appendix B

This appendix explains the sources, the method and procedures used to create the database. The database is composed with daily, monthly, quarterly and annual series. This paper uses monthly data. **Sources:**

- FRED
- IMF
- OECD
- WORLDECONOMICS

- Each data series was plotted and examined for anomalys and respective descriptive statistics analysed. This paper interpolated monthly data in case of missing points. The linear interpolation is done with the help of python (numpy, pandas, sklearn) as well as the SVM model and the plots (Matplotlib). The source code is available on[7]

Table 6: Starting date of the series used

	3-month interbank rate	**10-year Gov. bond yield**	**GDP in US$**	**GDP Growth rate**	**OECD recession**
Frequency	Monthly	Monthly	Annual	Quarterly	Monthly
FRANCE	1970 M1	1970 M1	1970	1970 Q1	1970 M1
GERMANY	1970 M1	1970 M1	1970	1970 Q1	1970 M1
IRELAND	1984 M1	1970 M12	1970	1970 Q1	1970 M1
ITALY	1978 M10	1991 M3	1970	1970 Q1	1970 M1
NETHERLANDS	1982 M1	1970 M1	1970	1970 Q1	1970 M1
SPAIN	1977 M1	1980 M1	1970	1970 Q1	1970 M1

Table 7: Descriptive statistics of seasonally adjusted monthly GDP growth rate including synthetic GDP growth

1970-17	**G_DEU**	**G_ESP**	**G_FRA**	**G_GBR**	**G_IRL**	**G_ITA**	**G_NLD**	**G_WAV**
count	571	571	571	571	571	571	571	571
mean	0.51	0.64	0.53	0.56	1.13	0.44	0.58	0.54
std	0.83	0.72	0.51	0.80	1.26	0.85	0.92	0.56
min	-4.49	-1.92	-1.64	-2.73	-3.84	-2.75	-4.91	-2.62
25%	0.07	0.27	0.24	0.24	0.54	0.00	0.15	0.31
50%	0.51	0.70	0.52	0.62	1.07	0.41	0.65	0.54
75%	0.99	1.01	0.85	0.94	1.77	0.85	1.02	0.83
max	3.98	3.78	1.99	4.95	7.04	5.99	5.82	2.43

[7] https://github.com/exzod/BSc-Thesis-

Table 8: Start and end of all recessions in the Eurozone according to OECD

Recession	
Start	End
1970/09	1972/03
1974/02	1975/06
1977/01	1977/09
1980/02	1982/12
1985/10	1987/03
1991/03	1993/08
1995/05	1997/01
1998/02	1999/01
2001/02	2003/07
2008/03	2009/06
2011/06	2013/03

- **Aggregation method:**
  - Annual GDP in US$ is transformed in percentages per country. The weighted average (synthetic yield and GDP growth) is the sumproduct of relative GDP weight and coresponding series (3-month rate, 10-year rate and GDP growth).

Table 9: Average GDP weight for each country used in construction of the synthetic (yield and GDP growth rate)

1970-2017	DEU	ESP	FRA	GBR	IRL	ITA	NLD
Mean	28.9%	8.4%	20.6%	18.9%	1.2%	16.1%	5.9%

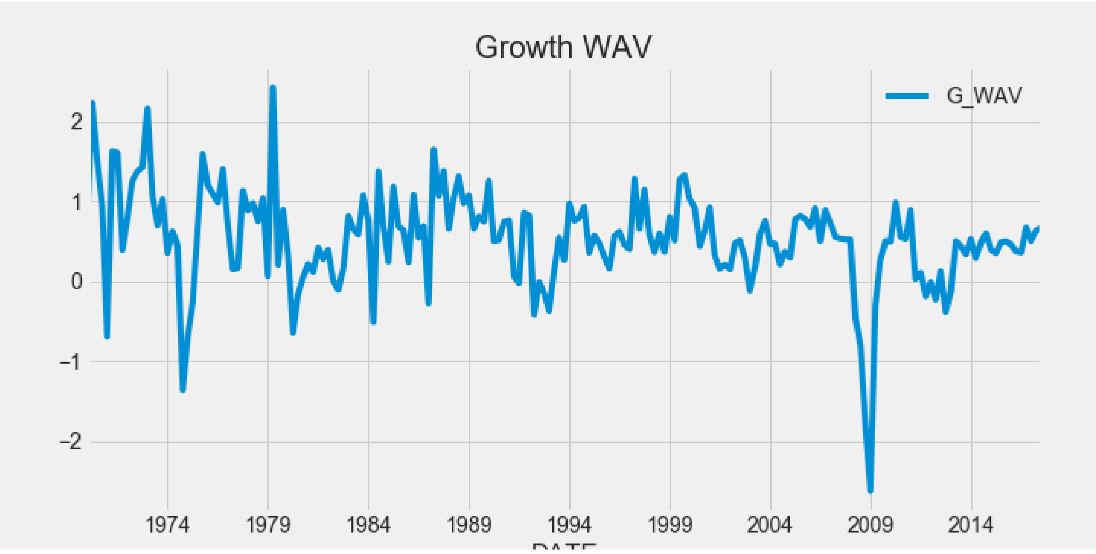

Figure 7: Visual representation of synthetic GDP growth rate fluctuations from 1970 to 2017