

*Mohr, Oliver*

*Monetary Policy at the Zero Lower Bound*

**Dissertation**  
**for obtaining the degree of Doctor of Business and Economics**  
**(Doctor rerum politicarum - Dr. rer. pol.)**

**at WHU – Otto Beisheim School of Management**

*3/31/2020*

**First Advisor:** *Professor Dr. Ralf Fendel*

**Second Advisor:** *Professor Dr. Michael Frenkel*

## Contents

<b>1. Introduction</b> .....	<b>1</b>
<b>2. Recession Probabilities for the Eurozone at the Zero Lower Bound: Challenges to the Term Spread and Rise of Alternatives</b> .....	<b>3</b>
2.1 Literature on Recession Probabilities .....	4
2.2 Conceptual Challenges to the Term Spread at the Zero Lower Bound .....	6
2.3 Set-up and Data of the Recession Model .....	7
2.3.1 <i>Model Set-up</i> .....	7
2.3.2 <i>Data</i> .....	8
2.3.3 <i>Measurement of Results</i> .....	10
2.4 Results of the Benchmark Model .....	12
2.5 Results of the Submodels .....	19
2.5.1 <i>Submodel 1 – Monetary Transmission Channels</i> .....	19
2.5.2 <i>Submodel 2 – Bivariate Specification</i> .....	22
2.5.3 <i>Submodel 3 – Unstable Surge</i> .....	24
2.6 Out-of-Sample Analysis and Varying Time Horizons .....	28
2.6.1 <i>Out-of-Sample Analysis</i> .....	28
2.6.2 <i>The Benchmark Model over Various Time Horizons</i> .....	28
2.6.3 <i>Submodels over Various Time Horizons</i> .....	29
2.7 Concluding Remarks on Recession Probabilities .....	31
<b>3. The Shape of Euro Area’s Uncertainty: Its Impact and Predictive Value on GDP</b> .....	<b>32</b>
3.1 Literature on Economic Uncertainty .....	33
3.1.1 <i>Consumers</i> .....	33
3.1.2 <i>Corporations</i> .....	34
3.1.3 <i>Financial Market Participants</i> .....	36
3.1.4 <i>Shape of Uncertainty</i> .....	37
3.2 Set-Up and Data of Economic Uncertainty .....	38
3.2.1 <i>Moments of Uncertainty</i> .....	38
3.2.2 <i>Economic Agents</i> .....	40
3.2.3 <i>Construction of the VAR and the Impulse Response Functions</i> .....	45
3.2.4 <i>Out-of-Sample Assessment of Forecast Accuracy</i> .....	46
3.2.5 <i>Validation of Results</i> .....	46
3.3 The Effects of Economic Uncertainty .....	46
3.3.1 <i>Behavior of the Different Moments</i> .....	47
3.3.2 <i>The Effect of Uncertainty on GDP</i> .....	52

3.4 Predictive Value of Uncertainty in GDP Forecasts .....	54
3.4.1 Results of the Different Forecasting Models .....	54
3.4.2 Purging for the Exogenous Component of the Second Moment .....	56
3.5 Concluding Remarks on Economic Uncertainty .....	57
<b>4. The Effect of the ECB’s Forward Guidance on Interest Rate Forecasts .....</b>	<b>58</b>
4.1 The ECB’s Forward Guidance .....	60
4.2 Transmission Channels of Forward Guidance .....	61
4.3 Interest Rate Predictability under Forward Guidance .....	62
4.4 Data and Methodology .....	64
4.4.1 Definition of the Error Term .....	64
4.4.2 Purging the Error Term from External Influences .....	66
4.4.3 Definition of Forward Guidance .....	66
4.5 The Effects of Forwards Guidance.....	67
4.5.1 The Observable Forecast Error .....	68
4.5.2 Assessment of the Exogenous Prediction Error .....	70
4.5.3 Quantification of the Effect of Forward Guidance on the Prediction Error .....	73
4.6 Robustness Tests .....	76
4.6.1 Prediction Error for the Level and Slope Forecast with Different Maturities .....	76
4.6.2 Alternative Starting Date of FG .....	77
4.7 Concluding Remarks on the Effect of Forward Guidance .....	78
<b>5. Conclusion.....</b>	<b>79</b>
<b>References .....</b>	<b>82</b>
<b>Appendix.....</b>	<b>88</b>

# 1. Introduction

In the aftermath of the Global Financial Crisis (GFC), the European Central Bank (ECB) was confronted with an economic and financial environment that has required a continuous evolution of the strategy and the implementation of monetary policy. The need for higher flexibility in central banking and monetary policy in the euro area can be traced back to both a shift of the economic paradigm seen in most developed nations over the last 15 years as well as to characteristics that are unique to the euro area. First, all major developed economies have remained in a liquidity trap with downward rigidity of nominal interest rates at the zero lower bound at least for several years after the GFC. This has resulted in an impairment of the most orthodox instrument of monetary policy - the short-term interest rate. Second, central banks have been historically concerned with fears of an inflation overshoot which they fought by pre-emptive tightening into the economic upswing. This time, however, inflation has remained below target for most developed nations with deflationary tendencies representing the primary concern: Ageing demographics, lower bargaining power of labor unions, a global savings glut and further technological advancements on the supply side increase the likelihood that the primary goal of monetary policy in the euro area will see increased left-tail risks for the inflation target. Third, the euro area is unique compared to other currency areas given the risk of a potential break-up of the currency union. During the first years of the euro area, markets assumed an implied guarantee of government debt for all issuers, which radically changed in the run-up to the European peripheral debt crisis resulting in the double dip recession of 2011 to 2013. Rooted in economic heterogeneity between core and peripheral Europe, investors are remaining cautious about the institutional and political will of Europe to preserve the euro in its current form. These paradigm shifts have required the ECB to expand their monetary policy toolkit and navigate in uncharted waters, necessitating a clear understanding of two perspectives: First, the central bank needs to accurately monitor and assess the current stance of the economic cycle and economic agents. Secondly, new monetary policy tools need to be assessed regarding their effectiveness. The goal of this dissertation aims at providing additional insights into both areas.

The first research topic covered in chapter 2 will focus on the probability of recession within the euro area. A more accurate understanding of the later stages of the economic cycle is vital for central banking given the time lag of its monetary policy decisions. We identify the best performing indicators for a recession within the next 12 months based on 43 underlying

single variables and different transformation including bi-variate specifications, monetary transmission channels and the modeling of unstable dynamics in the economy. In particular, we try to validate conventional indicators of recessions to understand whether a different economic and financial environment calls for a revised perspective on the business cycle. The analysis is extended over various forecasting horizons and we introduce risk-affine and risk-averse agents as reference point for evaluating the performance of the indicators.

The second research topic covered in chapter 3 examines the role of uncertainty in the context of the business cycle. As economic growth after the GFC has remained in lackluster territory for several years, the economic momentum has been more vulnerable to potential uncertainty shocks. Hence, the degree of confidence among economic agents, including consumers, corporations and financial markets, is representing a significant transmission channel of monetary policy. Hence, this section tries to gain a holistic understanding of uncertainty across these three economic groups and the four different moments of the uncertainty distribution. Based on this taxonomy, we construct various uncertainty indices and assess the impact on real GDP via impulse response functions and further investigate their informational value in rolling out-of-sample GDP forecasts.

The third research topic covered in chapter 4 examines the effectiveness of forward guidance of the ECB officially introduced on July 4<sup>th</sup>, 2013. The study analyzes the impact of forward guidance on the forecast error of financial markets participants regarding the interest rate level and the slope of the yield curve. We refer to OIS forwards (overnight index swap) as the relevant forecasts and purge the prediction error of several macroeconomic and financial variables to gain a pure representation of the exogenous forecast error. To quantify and isolate the effect of forward guidance, this study refers to the absolute deviation of forecasts from actual rates and further controls for variables representing unconventional monetary policies. In addition, we test for a revised starting date of forward guidance based on the “whatever it takes” speech by Mario Draghi on July 26<sup>th</sup>, 2012.

## 2. Recession Probabilities for the Eurozone at the Zero Lower Bound: Challenges to the Term Spread and Rise of Alternatives<sup>1</sup>

The literature on predicting the likelihood of a recession provides broad consensus on the term spread as a reliable indicator for the binary state of the business cycle. Almost two decades after the formation of the European Monetary Union (EMU), data on the currency bloc challenges conventional indicators given several dichotomies: A rather classical economic cycle characterized by the build-up of current account imbalances and economic overheating before the GFC was followed by a lackluster economy lingering in a liquidity trap and secular stagnation thereafter (Summers (2016)). The different monetary regimes were ranging from orthodoxy and hawkish mistakes to unconventional monetary policy with a main refinancing rate pinned down at the zero lower bound (ZLB) in an environment where the neutral interest rate has declined substantially over time (Laubach and Williams (2015)). In addition, the brief history of the EMU is unique compared to other currency areas and the cohesiveness of the underlying economic region has been hostage to politicians, monetary policy makers and financial markets. The re-pricing of risks through periods of substantial convergence of EMU countries and increasing frictions after the GFC has affected financial market variables beyond their predictive value vis-à-vis the business cycle. These particularities of the euro area require that predictors of recession and expansion phases need to be sensitive enough to detect different types of economic cycles and to be robust enough to withstand the effects of varying central bank policies.

The main purpose of this chapter is to assess the likelihood of a recession in the euro area within the next 12 months along four dimensions: The first dimension focuses on the selection and the relevant transformation of input factors in univariate probit models representing the benchmark model of the analysis. On a second dimension, this chapter introduces three submodels: First, we establish monetary transmission channels via principal component analysis to remove idiosyncratic influences and increase the indicators' robustness. Second, we combine the most predictive indicators from the benchmark model to identify paramount combinations. Third, we aim at modelling animal spirits and hawkish mistakes by constructing *unstable surge* indicators based on the deviation of the time series to its Hodrick-Prescott trend. The third dimension extends the analysis to three additional time horizons to analyze the lead-time of the input factors for the 6m, 18m, 24m forecasting

---

<sup>1</sup> This chapter is based on: Fendel et al. (2018): Recession Probabilities for the Eurozone at the Zero Lower Bound: Challenges to the Term Spread and Rise of Alternatives, Unpublished WHU Working Paper Series No. 18-04. A shorter version of the working paper was published at vox.eu (Fendel et al. (2019a)).

periods. The fourth dimension models the utility for risk-affine and risk-averse market participants based on a loss-function to identify their preferred choices.

The paper proceeds as follows: In section 2.1, a literature review sheds light on empirical findings. Section 2.2 discusses theoretical considerations on why the term spread might be prone to issue ambiguous signals in the current environment. Section 2.3 discusses the methodology and the dataset of the analysis. Section 2.4 reviews the benchmark model which is extended to the various submodels in section 2.5. Section 2.6 examines various time horizons and presents the results of an out-of-sample analysis. The chapter concludes with a summary of key findings in section 2.7.

## **2.1 Literature on Recession Probabilities**

Given the binary classification of the business cycle into recessions and expansion phases, statistical procedures to predict the state of economic activity are inherently non-linear with probit models representing the most popular regression specification.<sup>2</sup> As the literature remains inconclusive about a superior type of modification<sup>3</sup>, the main pivots for raising the predictive power of forecasting models have been the choice of input factors and their transformations. Hence, this section will classify existing studies on recession probabilities into their findings on the best performing explanatory variables, their regional perspective as well as their performance across various forecasting horizons and different transformations.

Regarding the explanatory variables, the slope of the yield curve has been associated with paramount predictive power for the future state of the business cycle. According to Estrella and Hardouvelis (1991), a positive term spread is a leading indicator for an expansion of consumption and production. Higher long-term interest rates signal higher demand for capital going forward due to higher future demand for investment and consumption. These results are underpinned by more recent research by Chauvet and Potter (2005), Rudebusch and Williams (2009) and Fornari and Lemke (2010). While the term spread has delivered strong predictive power across different pivots, Moneta (2005) examines ten variations of the yield curve (attachment points: 3m, 1yr, 2yr, 5yr, 10yr) and identifies the slope between the 3m and 10yr interest rate maturities as the most explanatory specification. Notwithstanding its widespread use, the term spread shows certain instability as the momentum of its inversion in the run-up to a recession can vary significantly with the type of economic downturn.

---

<sup>2</sup> A few studies also include logit regressions that produce similar results with slightly fatter tails of the probability distribution.

<sup>3</sup> Modifications to probit models yield partial improvements of results by including numerous states of the business cycle via multiple breakpoints in Markov-switching models (Dueker (1997), Levanon (2011), Chauvet and Potter (2005)), and VAR-augmented specifications (Fornari and Lemke (2010)).

The inclusion of additional variables in multivariate probit models yields improved results. King et al. (2007) show that bivariate models of the investment grade (IG) or high-yield (HY) corporate bond spread in combination with the yield curve reduce the occurrence of false positive signals significantly. Based on theoretical considerations of Gilchrist and Zakrajšek (2012), Ergungor (2016) decomposes the corporate bond spread, which is the additional yield for corporate bonds above the risk-free yield, into two parts that reflect the expected default of the issuer<sup>4</sup> and a general excess bond premium measured as the difference between the corporate spread and the expected default premium. While the excess bond premium turns out to be highly significant in predicting recessions, the additional yield implied by expected defaults does not display statistical significance. Confirming the predictive power of corporate bond spreads, Fornari and Lemke (2010) also ascribe stock returns the ability to augment the forecasting performance of the term spread. In an analysis to predict economic turning points, Dovern and Ziegler (2008) find that corporate spreads, survey data, and composite indicators of real economic variables increase the forecasting quality. However, the authors cast doubts on stock returns that issue multiple false signals. In a study by Liu and Moench (2014), the term spread is paramount over various time horizons and its performance increases most notably in combination with the 1yr change of the S&P 500, Broker-Dealer margin accounts, the ISM (Institute of Supply Management) new order index and the NAPM (National Association of Purchasing Managers) index of consumer commodity prices. An additional source of useful indicators stems from the universe of corporate financial data such as the dividend yield (Bellego and Ferrara (2009)) and pre-tax corporate profits (Ergungor (2016)) whose interpretation is vulnerable to the informationally dilutive effect of the USD exchange rate.<sup>5</sup>

While aforementioned variables possess rather unambiguous correlation with the business cycle, the literature also identified a number of factors whose sign seems to be dependent on the respective region. As the majority of studies on recession probabilities focuses on the U.S., some researchers extend their perspective to a multi-country panel (Fornari and Lemke (2010) and Haltmaier (2008)), and only a few focus explicitly on the euro area or selected EU countries (Moneta (2005) and Bellego and Ferrara (2009)). According to Haltmaier (2008), exchange rates are broadly significant, but the sign of their coefficients is ambiguous. While a real depreciation has mostly signaled a loss of confidence for developing

---

<sup>4</sup> The expected default rate is calculated based on historical sensitivities by relating the risk spread and actual defaults.

<sup>5</sup> As the USD serves as a flight to quality currency, the J-curve effect could lead to an initial increase in the sales value despite a deterioration of the economic environment.

countries (for example Mexico) coinciding with negative growth rates, in contrast a real appreciation has increased the recession probability for the UK and Taiwan whose open economies are more vulnerable to a loss of price competitiveness vis-à-vis the world. The same study shows that oil prices are significant for a selection of countries (U.S., the UK, Korea, and Taiwan) and insignificant for Canada and Mexico. A theoretical explanation lies in the cost-push effect for oil importing countries and the corresponding income-enhancing effect for oil-exporting nations. Variables falling short of predicting recessions have been gold prices, silver prices, treasury rates (King et al. (2007)) and monetary aggregates (except for M1). In particular, the forecasting power of real M2 has been in retreat since the late 1980s (Levanon et al. (2011)). The authors even identify a relationship that is inverse to the assumed causality with an increase of real M2 during the recession of 2001 and the GFC, potentially caused by de-regulation and structural changes of the banking sector.

The forecasting horizons covered by literature range from now-casting to up to 24 months. While results deteriorate for longer horizons, the predictive power of variables is the strongest for forecasting periods up to 12 months. However, shortening the forecasting horizon does not necessarily lead to improved results as the key determinant is the duration of the lead-time of the variable vis-à-vis the business cycle. Explanatory variables enter into statistical models as levels, changes over certain time periods (mostly 6m or 12m change) and lagged values. Procedures to reduce the dimensions of datasets have become increasingly popular. Predominantly based on principal component analysis, the use of indices as input factors yields the benefit of at least partly removing idiosyncratic characteristics of the underlying dataset (Levanon et al. (2011) and Chen et al. (2008)).

## **2.2 Conceptual Challenges to the Term Spread at the Zero Lower Bound**

From a conceptual perspective, the yield curve draws its explanatory value from two reinforcing sources: First, the inversion of the yield curve can be interpreted as a downward revision of market expectations on future real and nominal interest rates in the light of a decelerating economy. In line with the market expectations hypothesis, a decline of the long end of the interest rate curve reflects lower inflation expectations and dovish central bank policy that will be priced in at the first signs of a looming recession.

The second source of a flattening of the yield curve is monetary tightening in the boom phase of an economic cycle in order to contain inflationary pressures. As central banks have engaged in monetary tightening to tackle inflation, short-term interest rates tend to rise

faster than nominal interest rates in the mid-to-late cycle stage of an expansion, leading to a flattening of the curve.

At the ZLB, however, the shape of the yield curve as a predictor of the future state of the business cycle is compromised from two angles: The increasing use of forward guidance by central banks due to a change in monetary policy and a higher importance of the market segmentation theory in light of massive central bank asset purchases. Regarding the first aspect, central banks have indicated that future short-term interest rates would remain subdued for a pro-longed period of time, which was reflected by investors through declining forward rates and a related fall of the term spread. As a response, conventional recession models using the term spread would be signaling elevated probabilities of an economic downturn. Instead, the cause for the flattening of the interest rate curve is actually a new monetary policy instrument in a low-growth environment to escape the liquidity trap given dysfunctional fiscal and economic policy (Krugman (1998)).

The second differentiating characteristic at the ZLB is higher importance of the market segmentation hypothesis. While certain investors such as foundations, retail clients and hedge funds are less bound to certain maturity segments and asset classes, other investor groups like pension funds, insurance companies and foreign central banks are reliant on government bonds and certain maturity segments that serve their quality, liquidity and asset-liability matching needs – particularly at longer maturities. As these investors tend to stick to their preferred habitat, a central bank can create downward pressure on these market segments without above-mentioned investors rotating out of these market segments. Given that the main refinancing rate has already been at the ZLB with corresponding downward rigidity, the market segmentation hypothesis contributed to the observed flattening of the interest rate curve without providing actual information about the future state of the business cycle.

## **2.3 Set-up and Data of the Recession Model**

### **2.3.1 Model Set-up**

Research on recession probabilities refers commonly to the standard probit model specification to capture the binary state of the dependent variable and the continuous nature of input factors:

$$P(Y_{with} (t+k)) = \theta (\alpha_0 + \alpha_1' X_t), \quad [ 1 ]$$

where  $Y$  describes the binary state of the business cycle within the next  $t+k$  months. If one of the next 12 months is defined as a recession month,  $Y$  takes the value of 1, otherwise, it is 0. The probit model is based on the standard normal cumulative density function  $\theta$ . Thus, the model assumes non-linear behaviour of recession probabilities.  $\alpha_0$  denotes a constant term and  $\alpha_1$  represents the coefficients for the vector  $X_t$  which contains the input factors. In order to avoid over-specification and to be parsimonious, the following analysis only estimates univariate and bivariate models. As compared to recession models that forecast the probability of a downturn “in” 12 months, this analysis is more useful in detecting the actual length of a recession at the expense of the leading nature of the model.<sup>6</sup> As a remedy for this statistical trade-off, the analysis explicitly considers the 6m, 18m and 24m forecasting horizons to vary the lead-time of the calibration.

The baseline model of this paper covers a univariate specification of the standard probit regression and considers three transformations of the input factors (the level, the 6m change and the 12m change).<sup>7</sup> In addition, the analysis establishes three submodels: The first submodel uses monetary transmission channels as input factors derived from principal component analysis; the second submodel focuses on identifying superior bivariate model specifications; the third submodel aims at detecting unstable economic developments to increase the lead-time of recession signals. The exact set-up of each submodel will be explained in greater detail in the sections 2.5.1, 2.5.2 and 2.5.3.

### **2.3.2 Data**

The analysis covers monthly observations for the time period between December 2001 and December 2017 based on data from Bloomberg and Haver. The binary dependent variable relies on the quarterly classification of the CEPR euro area Business Cycle Dating Committee which indicates that 33 months out of a total of 193 are classified as recession months.<sup>8</sup> The Committee defines a recession as “*a significant decline in the level of economic activity, spread across the economy of the euro area, usually visible in two or more consecutive quarters of negative growth in GDP, employment and other measures of aggregate economic activity for the euro area as a whole.*” The concept to rely on a number of characteristics increases the resilience of the classification towards data revision and economic relevance.

---

<sup>6</sup> Whether a recession signal is considered as correct or not depends on a time frame and not a specific moment in time.

<sup>7</sup> If the concept of the indicator does not allow for stationarity, the level is not included in the analysis.

<sup>8</sup> Given the limited history of the euro area, we associate single months with the quarterly classification of the CEPR instead of aggregating the monthly input factor to quarterly periodicity.

As we focus on the probability of an economic downturn *within* a certain time period, the list of recession observations is modified to reflect the various forecasting horizons of 6m, 12m, 18m and 24m.<sup>9</sup> The underlying dataset for the 43 explanatory variables [see Table 1 for the complete list] can be broadly classified into eleven categories: interest rates, the term spread, money supply, competitiveness, sentiment, refinancing conditions, preference for risk, industrial data, inflation, commodities, and the wealth channel.

**Table 1: List of Input Factors for the Benchmark Model**

Variables	Source	Code	Transformation	Comment
<b>Rates</b>	3m EURIBOR	Haver	N023RI3E@G10	***
	10yr German Government Bond	BBG	GTDEM10Y Govt	***
<b>Term Spread</b>	Term Spread: 10y-3m	BBG / Haver	10yr: GTDEM10Y /3m: N023RI3E@G10	***
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate]	Haver	N023SHDW@G10	***
<b>Money Supply</b>	M1	Haver	S023FM1@G10	**
	Real M1	Haver	Inflation: H025PCXG@G10	**
	M2	Haver	S023FM2@G10	**
	Real M2	Haver	Inflation: H025PCXG@G10	**
	M3	Haver	S023FM3@G10	**
	Real M3	Haver	Inflation: H025PCXG@G10	**
<b>Competitiveness</b>	FX EUR/USD	Haver	N023XUNE@G10	***
	JPM Nominal Broad Effective FX Rate	Haver	N023XJNB@G10	***
	Terms of Trade	Haver	H025PFTT@G10	*** Time lag of 2 months
<b>Sentiment</b>	PMI	Haver	M023TG@MKTPMI	***
	Economic Sentiment	Haver	S025VES@G10	***
	Industrial Confidence	Haver	S025VB@G10	***
	Consumer Confidence	Haver	S025VCC@G10	***
	Consumer Economic Situation	Haver	S025VCE@G10	***
	Business Climate	Haver	S025VBC@G10	***
<b>Refinancing</b>	Corporate Bonds: Investment Grade Spread	Barclays	2002	*** Option-adjusted spread
	High Yield Spread	ICE	HPC4	*** Option-adjusted spread
	EZ Peripheral Bond Spread	BBG	BBG 10yr generic yields of DE/IT/ES/GR/IE/PT	*** Country weighting of 2017 = 2016 given GDP publication lag; Greece is included since 2009
	MFI Loans to Private Sector	Haver	S023FCB@G10	**
<b>Risk Aversion</b>	Implied Rates Volatility	BBG	EUNEF10 ICPL/ EUSN0F10 / EUSV0F10	***
	VSTOXX	BBG	V2X Index	***
	VIX	BBG	VIX Index	***
	FX Basis EUR/USD	BBG	EUBS1 Index	***
	Implied FX Vol	BBG	EURUSDV1M Index	***
	LiborOIS	BBG	BICLOIS5 Index	*
<b>Industrial Data</b>	Industrial Production: Industry excl. Constr.	Haver	S025D@G10	** Time lag of 1 month
	Unemployment Rate	Haver	S023ELUR@G10	*** Time lag of 1 month
	Manufact. New Orders	Haver	S025TO@G10	** Time lag of 1 month
	Industr. Turnover: Manufacturing	Haver	S025TS@G10	** Time lag of 1 month
	Mfg Stocks of Finished Products	Haver	S025TI@G10	***
	Retail Sales	Haver	S025TRSC@G10	** Time lag of 1 month
	New Passenger Cars	Haver	H025CVRT@G10	**
<b>Inflation</b>	HICP	Haver	H023PC@G10	**
	HICP excl. Energy, Food, Alcohol & Tobacco	Haver	H025PCXG@G10	**
	Domestic PPI: Industry excluding Construction	Haver	H025PP@G10	** Time lag of 1 month
<b>Commodities</b>	Crude Oil	BBG	CL1 Comdty	***
	Gold	BBG	XAU Comdty	***
<b>Wealth</b>	ESTOXX50	Haver	N023FKAE@G10	**
	Residential Building Permits	Haver	S025HP@G10	** Time lag of 1 month

\* Level; \*\* 6m and 12m change; \*\*\* Level, 6m and 12m change

Input factors enter into the probit model with various transformation, explained via \*, \*\*, \*\*\*.

Source for code: Haver

Abbreviations: FX = Foreign Exchange Rate; ESTOXX = EuroSTOXX; EZ = Eurozone; HICP = Harmonised Index of Consumer Prices; PMI = Purchasing Manager Index; PPI = Producer Price Index;

The first three groups represent traditional channels of central bank policy via direct control of short-term *interest rates* and the *monetary base* as well as indirect control of the *shape of*

<sup>9</sup> For example, the definition of a recession „within six months” requires the binary variable to signal a recession at time  $t=0$  if  $t+5$  is a recession month, although the economy might expand in  $t+6$ .

*the yield curve*. To account for the downward rigidity of interest rates at the ZLB, a modified version of the term spread considers a shadow short-term rate (Wu and Xia (2016)) that allows for reaching deeply negative territories. The remaining eight segments of variables extend the narrow view of conventional central bank measures to a more diverse group of monetary transmission mechanisms.

Varying in their leading, coinciding or lagging nature vis-à-vis the business cycle, the time series are selected based on the existing literature and theoretical considerations about their predictive quality. In addition to the level of the respective variables, the study includes their 6m and 12m changes<sup>10</sup> to allow for different levels of sensitivity and to ensure reasonably mean-reverting characteristics in light of potential structural breaks.

### 2.3.3 Measurement of Results

Following the recent shift in literature away from model evaluation based on fit indicators<sup>11</sup> to its actual classification ability, this paper assesses the quality of results from three different angles: A signaling approach (Kaminsky and Reinhart (1999)), the area under the receiver operating curve (AUROC) and a loss function to model risk-averse and risk-seeking investors (Alessi and Detken (2009)).

The first criterion assumes that an indicator signals a recession when it surpasses the 50% threshold. Based on four categories, the signal is classified according to following matrix (Kaminsky and Reinhart (1999)):

	<b>Recession within 12m</b>	<b>No Recession within 12m</b>
<b>Signal: Recession</b>	A	B
<b>Signal: No Recession</b>	C	D

We will discuss indicators along a variety of performance ratios, including the number of recession months detected, false alarms and the overall percentage of correct predictions.<sup>12</sup>

As a remedy for the intuitive but somewhat arbitrary choice of the 50% threshold, this paper considers the area under the receiver operating curve (AUROC) as an alternative

<sup>10</sup> We either use the absolute difference between levels (“diff”) or the %-change between levels.

<sup>11</sup> To assess the quality of results, models have predominantly relied on fit indicators such as the Bayesian Information Criterion (King et al. (2007)), different versions of R<sup>2</sup> (Chen et al. (2008) and Moneta (2005)) and other loss functions like quadratic/logarithmic probability scores (Chauvet and Potter (2005) and Levanon et al. (2011)).

<sup>12</sup> The definitions of the various performance ratios are given in the heading of the respective performance tables.

criterion. First introduced by Birdsall and Peterson (1953), this method was developed to express the diagnostic ability of a binary classifier system and has been recently used to describe the classification ability of business cycle indicators (Berge and Jordà (2011) and Liu and Moench (2014)). The centerpiece of this method is the receiver operating curve (ROC) which describes the ratio of true positive signals to false positive signals at various threshold values.

1. This method defines evenly spaced cut-off points, denoted as  $\Omega$ , which determine whether to interpret the indicated likelihood  $p$  as a recession or an expansionary signal. The narrower the cut-off points are, the smoother is the ROC curve. The example below assumes ten thresholds with a distance of 0.1.

$$\Omega = [0, 0.1, 0.2, \dots, 0.8, 0.9, 1]$$

2. For each cut-off point, the process determines the ratio of true positive signals (TPS) and the ratio of false alarms (FA).

$$TPS = \frac{1}{NR} \sum_{t=1}^T x; \text{ where } x = \begin{cases} 1, & p \geq \Omega; \text{ followed by a recession} \\ 0, & p < \Omega \end{cases}$$

where NR describes the number of recession months

$$FA = \frac{1}{NE} \sum_{t=1}^T z; \text{ where } z = \begin{cases} 1, & p \geq \Omega; \text{ followed by an expansion} \\ 0, & p < \Omega \end{cases}$$

where NE describes the number of expansion months

3. For each cut-off point, the procedure creates a coordinate in TPS-FA-space and connects these points to create the ROC. Coordinates above the 45% diagonal represent signals that are better than a random guess.
4. The AUROC is the integral of the area below the ROC.

The third criterion sheds light on the usefulness of indicators for different types of market participants following their relative preference of type 1 errors (missed recessions) versus type 2 errors (false alarm) along the lines of Alessi and Detken (2009). The one investor group that is rather sensitive to missing a recession will be labelled as *risk-averse*. The other group of market participants, described as *risk-affine*, is more concerned with false alarms which would detract from performance in the expansion phase. The loss function  $L$  of both investor groups is defined along the type I error and the type II error:

$$L = \rho \frac{C}{A+C} + (1 - \rho) \frac{B}{B+D} . \quad [2]$$

For the risk-averse investor group,  $\rho$  is assigned a value of 0.75, which issues a higher penalty for undetected recessions. For risk-affine investors, we assume  $\rho$  to be 0.25 (which causes a higher value for the loss function from false alarms).

## 2.4 Results of the Benchmark Model

This section highlights first the challenges that the regime change of monetary policy at the ZLB is creating for the empirical supremacy of the term spread. We further suggest a modification of the term spread and then proceed with a review of the best-performing indicators. Subsequently, the results are presented in a way that selected graphs displaying the recession probabilities are included as figures (with panels for the selected indicators) in the main text body. The more detailed statistics on all indicators also including our second (AUROC) and third criteria (the loss function) are presented in Figure 1 and the corresponding Table A1.

While the recession of 2008-2009 still serves as a prime example for the ability of the term structure to forecast an economic downturn with sufficient lead-time<sup>13</sup>, the indicator fails to capture the second recession beginning in 2011 [see Figure 1a]. To the contrary, the signal inches north in the aftermath of the European Sovereign Debt Crisis and remains elevated for the time period between 2015-2017 in the wake of a flattening of the interest rate curve induced by the Expanded Asset Purchase Programme by the ECB starting in 2015.

---

<sup>13</sup> The term spread signals a recession probability of above 50% as early as November 2006

# Figure 1: Univariate Benchmark Model – 12m Forecasting Horizon

Figure 1a

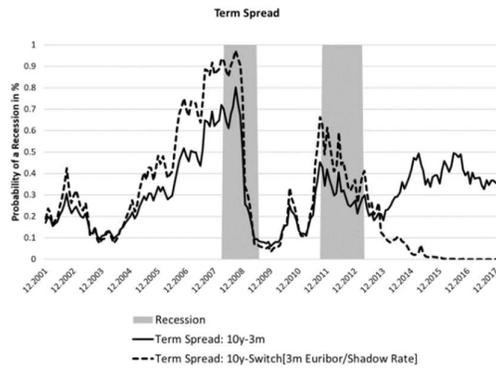


Figure 1b

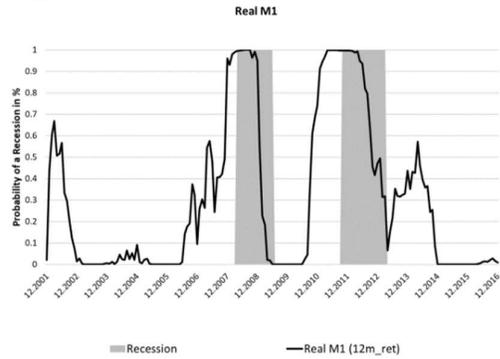


Figure 1c

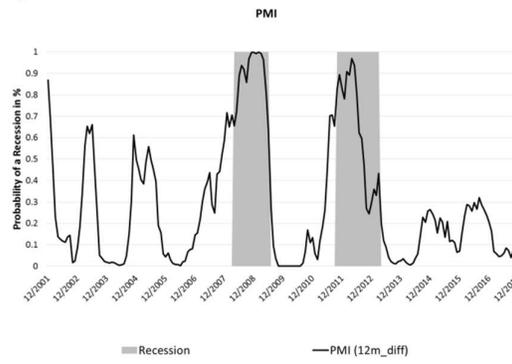


Figure 1d

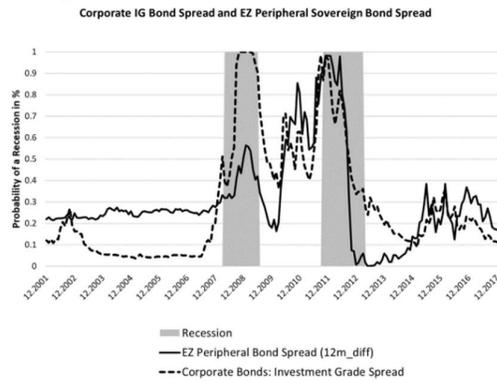


Figure 1e

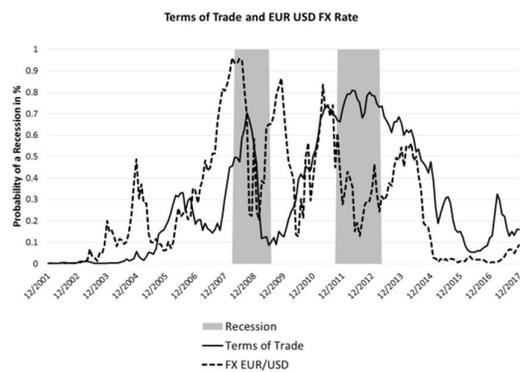


Figure 1f

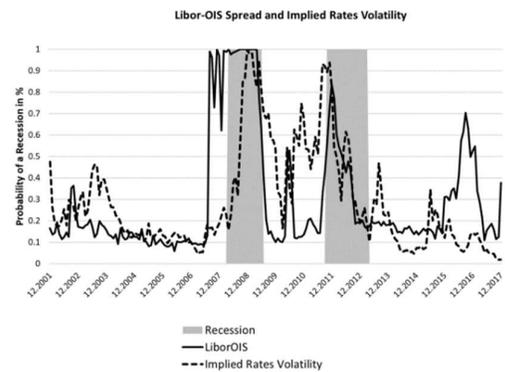


Figure 1g

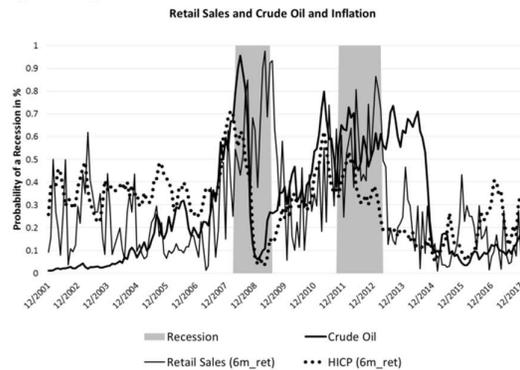
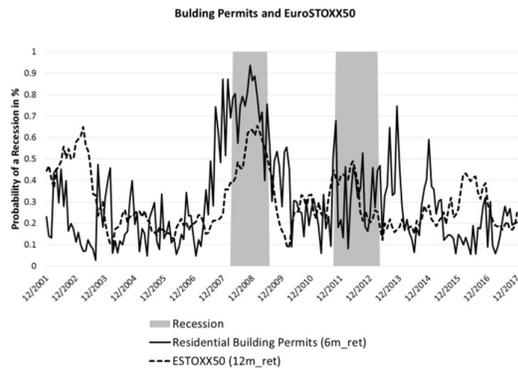


Figure 1h



**Table A1: Univariate Benchmark Model – 12m Forecasting Horizon**

12m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession		True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued No Signal Issued	A C	B D					L = 0.25	L = 0.75
Rates	3m EURIBOR			64%	80%	33%	0%	0.17	0.50
	3m EURIBOR (6m_diff)			46%	72%	9%	0%	0.23	0.68
	3m EURIBOR (12m_diff)			63%	70%	0%	0%	0.25	0.75
	10yr German Government Bond			53%	70%	0%	0%	0.25	0.75
	10yr German Government Bond (6m_diff)			52%	70%	0%	0%	0.25	0.75
	10yr German Government Bond (12m_diff)			53%	70%	0%	0%	0.25	0.75
Term Spread	Term Spread: 10y-3m			69%	78%	33%	2%	0.19	0.51
	Term Spread: 10y-3m (6m_diff)			53%	70%	0%	0%	0.25	0.75
	Term Spread: 10y-3m (12m_diff)			66%	70%	0%	0%	0.25	0.75
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate]			84%	80%	49%	7%	0.18	0.40
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (6m_diff)			57%	70%	0%	0%	0.25	0.75
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (12m_diff)			74%	72%	16%	4%	0.24	0.64
Money Supply	M1 (6m_ret)			84%	84%	62%	6%	0.14	0.30
	M1 (12m_ret)			94%	86%	69%	7%	0.13	0.25
	Real M1 (6m_ret)			85%	86%	65%	5%	0.12	0.27
	Real M1 (12m_ret)			95%	88%	73%	5%	0.10	0.22
	M2 (6m_ret)			52%	70%	0%	0%	0.25	0.75
	M2 (12m_ret)			53%	70%	0%	0%	0.25	0.75
	Real M2 (6m_ret)			49%	70%	0%	0%	0.25	0.75
	Real M2 (12m_ret)			50%	70%	0%	0%	0.25	0.75
	M3 (6m_ret)			51%	70%	0%	0%	0.25	0.75
	M3 (12m_ret)			53%	70%	0%	0%	0.25	0.75
	Real M3 (6m_ret)			49%	70%	0%	0%	0.25	0.75
	Real M3 (12m_ret)			51%	70%	0%	0%	0.25	0.75
Competitiveness	FX EUR/USD			84%	78%	49%	10%	0.20	0.41
	FX EUR/USD (6m_ret)			48%	70%	0%	0%	0.25	0.75
	FX EUR/USD (12m_ret)			53%	70%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate			67%	70%	16%	6%	0.26	0.64
	JPM Nominal Broad Effective FX Rate (6m_ret)			53%	70%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate (12m_ret)			61%	69%	0%	2%	0.26	0.75
	Terms of Trade			85%	78%	60%	13%	0.20	0.33
	Terms of Trade (6m_ret)			63%	70%	0%	0%	0.25	0.75
	Terms of Trade (12m_ret)			70%	70%	22%	10%	0.27	0.61
	PMI			69%	69%	4%	4%	0.18	0.45
	PMI (6m_diff)			80%	81%	51%	6%	0.17	0.38
	PMI (12m_diff)			88%	83%	60%	7%	0.15	0.32
Sentiment	Economic Sentiment			57%	72%	13%	2%	0.23	0.66
	Economic Sentiment (6m_diff)			82%	82%	56%	6%	0.16	0.34
	Economic Sentiment (12m_diff)			76%	81%	47%	5%	0.17	0.41
	Industrial Confidence			48%	70%	0%	0%	0.25	0.75
	Industrial Confidence (6m_diff)			81%	82%	51%	5%	0.16	0.38
	Industrial Confidence (12m_diff)			74%	74%	27%	6%	0.22	0.56
	Consumer Confidence			69%	75%	27%	5%	0.22	0.56
	Consumer Confidence (6m_diff)			77%	81%	51%	6%	0.16	0.38
	Consumer Confidence (12m_diff)			73%	78%	49%	10%	0.20	0.41
	Consumer Economic Situation			75%	83%	55%	5%	0.15	0.35
	Consumer Economic Situation (6m_diff)			76%	80%	47%	6%	0.18	0.41
	Consumer Economic Situation (12m_diff)			79%	80%	51%	8%	0.18	0.39
	Business Climate			48%	70%	0%	0%	0.25	0.75
	Business Climate (6m_diff)			81%	82%	51%	5%	0.16	0.38
	Business Climate (12m_diff)			75%	73%	25%	6%	0.23	0.57
	Corporate Bonds: Investment Grade Spread			85%	82%	56%	7%	0.16	0.35
	Corporate Bonds: Investment Grade Spread (6m_diff)			61%	77%	24%	0%	0.19	0.57
	Corporate Bonds: Investment Grade Spread (12m_diff)			78%	82%	44%	1%	0.15	0.42
Refinancing	High Yield Spread			76%	71%	25%	9%	0.25	0.58
	High Yield Spread (6m_diff)			65%	77%	31%	2%	0.19	0.52
	High Yield Spread (12m_diff)			76%	85%	55%	2%	0.13	0.35
	EZ Peripheral Bond Spread			74%	80%	45%	6%	0.18	0.42
	EZ Peripheral Bond Spread (6m_diff)			77%	71%	11%	2%	0.24	0.67
	EZ Peripheral Bond Spread (12m_diff)			85%	82%	49%	3%	0.15	0.39
	MFI Loans to Private Sector (6m_ret)			52%	70%	0%	0%	0.25	0.75
	MFI Loans to Private Sector (12m_ret)			58%	70%	0%	0%	0.25	0.75
	Implied Rates Volatility			79%	80%	51%	8%	0.18	0.39
	Implied Rates Volatility (6m_diff)			67%	73%	20%	4%	0.23	0.61
	Implied Rates Volatility (12m_diff)			71%	75%	24%	3%	0.21	0.58
	VSTOXX			66%	69%	13%	6%	0.27	0.67
VSTOXX (6m_ret)			56%	71%	5%	1%	0.24	0.71	
VSTOXX (12m_ret)			65%	71%	13%	4%	0.25	0.66	
VIX			73%	71%	22%	8%	0.25	0.61	
VIX (6m_ret)			58%	71%	11%	2%	0.24	0.67	
VIX (12m_ret)			70%	79%	40%	4%	0.18	0.46	
FX Basis EUR/USD			78%	75%	38%	9%	0.22	0.49	
FX Basis EUR/USD (6m_diff)			53%	70%	0%	0%	0.25	0.75	
FX Basis EUR/USD (12m_diff)			69%	76%	20%	0%	0.20	0.60	
Implied FX Vol			64%	76%	24%	1%	0.20	0.57	
Implied FX Vol (6m_ret)			57%	70%	7%	2%	0.25	0.70	
Implied FX Vol (12m_ret)			64%	71%	15%	5%	0.25	0.65	
LiborOIS			82%	82%	53%	6%	0.16	0.37	
Industrial Data	Industrial Production: Industry excl. Constr. (6m_ret)			65%	73%	15%	2%	0.23	0.64
	Industrial Production: Industry excl. Constr. (12m_ret)			52%	70%	0%	0%	0.25	0.75
	Unemployment Rate			58%	70%	0%	0%	0.25	0.75
	Unemployment Rate (6m_ret)			65%	71%	9%	2%	0.25	0.69
	Unemployment Rate (12m_ret)			56%	70%	0%	0%	0.25	0.75
	Manufact. New Orders (6m_ret)			65%	75%	18%	1%	0.21	0.62
	Manufact. New Orders (12m_ret)			55%	70%	0%	0%	0.25	0.75
	Industr. Turnover: Manufacturing (6m_ret)			54%	72%	9%	1%	0.23	0.68
	Industr. Turnover: Manufacturing (12m_ret)			60%	70%	0%	0%	0.25	0.75
	MFG Stocks of Finished Products			48%	70%	0%	0%	0.25	0.75
	MFG Stocks of Finished Products (6m_diff)			79%	78%	47%	8%	0.19	0.42
	MFG Stocks of Finished Products (12m_diff)			77%	78%	42%	6%	0.19	0.45
	Retail Sales (6m_ret)			83%	80%	45%	6%	0.18	0.42
	Retail Sales (12m_ret)			78%	76%	44%	10%	0.21	0.45
	New Passenger Cars (6m_ret)			69%	71%	13%	3%	0.24	0.66
	New Passenger Cars (12m_ret)			78%	77%	45%	10%	0.21	0.43
	HICP (6m_ret)			76%	77%	25%	3%	0.19	0.56
	HICP (12m_ret)			82%	83%	53%	3%	0.14	0.36
HICP excl. Energy, Food, Alcohol & Tobacco (6m_ret)			68%	65%	2%	0%	0.30	0.75	
HICP excl. Energy, Food, Alcohol & Tobacco (12m_ret)			69%	63%	0%	10%	0.32	0.77	
Domestic PPI: Industry excluding Construction (6m_ret)			72%	74%	15%	0%	0.21	0.64	
Domestic PPI: Industry excluding Construction (12m_ret)			80%	76%	51%	13%	0.22	0.40	
Commodities	Crude Oil			82%	78%	62%	15%	0.21	0.32
	Crude Oil (6m_diff)			47%	70%	0%	0%	0.25	0.75
	Crude Oil (12m_diff)			52%	70%	0%	0%	0.25	0.75
	Gold			76%	82%	49%	3%	0.15	0.39
	Gold (6m_diff)			58%	70%	2%	1%	0.25	0.74
	Gold (12m_diff)			68%	68%	2%	2%	0.26	0.74
Wealth	ESTOXX50 (6m_ret)			66%	71%	18%	6%	0.25	0.63
	ESTOXX50 (12m_ret)			69%	68%	16%	10%	0.28	0.65
	Residential Building Permits (6m_ret)			76%	77%	40%	6%	0.20	0.47
	Residential Building Permits (12m_ret)			74%	75%	35%	7%	0.22	0.51

“diff” describes the absolute difference between levels; “ret” describes the % change between levels;

In an attempt to restore the informational content of the yield curve, we suggest a modified version of the term spread [see Figure 1a] that incorporates the shadow rate<sup>14</sup> by Xia and Wu (2016) and removes the downward rigidity of the front-leg.<sup>15</sup> As quantitative easing (QE) at the ZLB can be perceived as a substitute for further rate cuts, this revised indicator is composed of a variable front-leg that switches from the 3m Euribor to the shadow rate as soon as the ECB's policy rate hits the ZLB.<sup>16</sup> Indeed, the ECB's unconventional monetary policy leads to a "shadow" steepening of the yield curve as the front-leg turns deep into negative territory. Hence, the average recession probability for the period between January 2015 and December 2017 recedes to 1% as compared to 40% as indicated by the traditional term spread.

The best performing indicator of the analysis is *real M1* (12m change), which reaches an almost perfect AUROC of 0.95, issuing 88% correct signals and detecting 73% of all recession months [see Table A1]. In the run-up to both recessions, the indicator crosses the 50% threshold already 12 months before the start of each economic downturn [see Figure 1b]. Interestingly, Real M1 signals heightened recession risks around the near-crisis period at the beginning of last decade where economic growth had been lingering in negative territory for three months. Notwithstanding the fact that this time period did not technically qualify as a recession, these false positive signals underline the sensitivity of Real M1 to the economic cycle. Other monetary aggregates, M2 and M3, prove not to be useful as they are missing the leading character and are more exposed to other structural forces.

Slightly trailing the classification ability of Real M1, the second best performing cohort of variables is composed of indicators from sentiment indices, refinancing conditions, and measures of competitiveness. As the best indicator of the *sentiment* variables, the 12m change of the Purchasing Managers Index (PMI) [see Figure 1c and Table A1] detects 60% of all crises with an AUROC of 0.88 and outperforms variables reflecting consumer or broader industrial surveys. Across all sentiment indices, the transformation to the 6m or 12m change has a significantly higher predictive value than the level due to a higher sensitivity to turning points. Regarding the recession of 2008-2009, the 12m change yields a lead time of 5m (3m for the second recession), while the level of the PMI first crosses a recession probability of

---

<sup>14</sup> The shadow rate represents a hypothetical short-term interest rate obtained through the extended Kalman filter, which is inferring the short-term rate based on the informational content of the medium to long-term part of the interest rate curve.

<sup>15</sup> To have a better comparison to the traditional version of the term spread, we use the EURIBOR instead of the EONIA as an input factor to the modified version.

<sup>16</sup> The ZLB is defined as the situation where the lending facility is at 0% and the main refinancing rate hits 0.25% effectively limiting the space for further cuts (13<sup>th</sup> November 2013).

50% when the economy is already four months in recession (signal is coinciding with the start of the second recession).

Within the group of *refinancing conditions*, both spreads of IG corporate bonds and euro area peripheral sovereign bonds provide strong results [see Figure 1d and Table A1]. Findings for the peripheral bond spread (12m change) indicate an AUROC of 0.85 and 49% of crisis detected. While the indicator is only somewhat flirting with the 50% threshold during the first recession, the variable issues strong recession signals as early as 16 months before the start of the second downturn, highlighting the causal relationship between tightening of financial conditions and economic growth in the euro area. This underlines the beneficial, dual characteristics of an indicator to reflect both a deteriorating endogenous business cycle and being itself a source for an exogenous shock. In light of the structural break in the wake of the euro area crisis<sup>17</sup>, it turns out to be preferable to use the differenced time series as model input instead of the level. Particularly from the perspective of a risk-affine investor, this variable seems to be of use as it is less prone to non-systemic fluctuations with only 3% false positive recession signals [see Table A1].

The IG corporate bond spread (level) yields an AUROC of 0.85 and detects 56% of recession months while issuing 7% false positive signals [see Table A1]. The indicator provides a lead-time of 1m before the GFC and 11m before the second recession. The underperformance of high yield (HY) corporate spreads lends support to the critique of Gilchrist and Zakrajšek (2012) who suggest that the excess bond premium, and not the default risk premium, is the informative component about the future state of the economy. Since HY spreads are influenced to a stronger degree by the idiosyncratic default risk component, the actual sentiment among investors is reflected to a lesser degree. Despite a lead-time of 4m before the GFC and 2m before the European peripheral crisis, the indicator proves to be less reliable due to the above-described idiosyncratic nature of the indicator.

In the *competitiveness* category, Terms of Trade detects 60% of crisis months with an AUROC of 0.85, moderately outperforming the FX EUR/USD rate (49% detected crisis and AUROC of 0.84) [see Figure 1e and Table A1]. The strength of this indicator stems from the ability to include various characteristics such as the trade-weighted FX rate, import and export elasticities and the relative price of exports and imports. The variable yields a lead-time of 10m before the European peripheral crisis and is coinciding with the first recession. Periods of deterioration in the Terms of Trade can be a consequence of several events: a) shifts of global

---

<sup>17</sup> The first half of the last decade was characterized by a convergence process of sovereign bond yields and the assumption by capital markets that government debt of the euro area countries carried an implicit guarantee.

liquidity out of the euro into USD-denominated safe haven assets b) higher commodity prices increasing production costs c) lower export prices depressing internal consumption and investments. All these potential drivers are associated with a decrease in real economic growth and the probit model, hence, considers a significant deterioration of the indicator as a harbinger of a recession. The early indicator appeals in particular to risk-averse investors who accept a relatively high number of false alarms of 13% in exchange for the third highest number of recession months detected.

Results for the other categories are overall mixed with some noteworthy exceptions. Out of the indicators reflecting *Preference for Risk*, the level of implied interest rates volatility yields an AUROC of 0.79 and detects 51% of all crises [see Figure 1f and Table A1]. While the indicator is only coinciding with the first recession, the variable remains elevated in the preceding 14 months<sup>18</sup> before the second economic downturn capturing the uncertainty in financial markets during the peripheral crisis of 2011-2013.

Two other indicators that are sensitive to investor's varying preference for risk are the Libor-OIS<sup>19</sup> spread (AUROC of 0.82 and 53% detected crisis) [Figure 1f and Table A1] and the EUR/USD FX Basis<sup>20</sup> (AUROC of 0.78 and 38% detected crisis; see Table A1). As an indicator for global risks, the Libor-OIS spread accurately signals the GFC with a lead of eight months. On the flipside of its global nature, the variable is only coinciding with the second economic downturn which was idiosyncratic to the euro area. At the end of 2016, however, the indicator reveals its vulnerability to dynamics surrounding the infrastructure of the interbanking market: The variable is falsely issuing a recession probability above 50% for seven consecutive months due to a U.S. money market reform that pushed U.S. investors from prime money market funds into U.S. treasuries. Likewise, the FX basis seems to generate reasonable results within the framework of this analysis. A closer look at the fundamental drivers, however, reveals three, conceptually different periods of basis widening: At the height of the GFC, the breakdown of the covered interest rate parity was primarily driven by interbank market stress and USD shortage (Borio et al. (2016)). The second period from 2011-2014 can be characterized by increasing redenomination risks in the euro area and the corresponding demand for USD vs. the euro as a safe haven currency. While the beginnings of both periods were associated with the start of the two recessions, the subsequent third period was merely a reflection of ECB excess liquidity following the accelerated bond

---

<sup>18</sup> The indicator dips briefly below the 50% threshold during those 14m.

<sup>19</sup> OIS stands for overnight indexed swap and is used as a reference point together with LIBOR rates to measure the health of the banking system.

<sup>20</sup> The cross-currency basis is the basis spread added to the USD LIBOR to re-establish the covered interest rate parity between the EUR and the USD.

purchase program.<sup>21</sup> Hence, the latest widening has erroneously sent out recession signals for most of 2016. Hence, we suggest the use of implied rates volatility as a more robust input factor over the Libor-OIS spread and the EUR/USD FX basis which are more immediate but also more prone to exogenous shocks that are unrelated to the business cycle. The category *Preference for Risk* performs clearly better for risk-averse investors due to the higher sensitivity than for the risk-affine investor type who perceives missing a crisis as less costly.<sup>22</sup>

The best performing variables in the *industrial data section* are retail sales (6m change) [see Figure 1g and Table A1], stocks of finished products (6m change) and new cars (12m change) with an AUROC between 0.78-0.83 and detected crisis between 45% and 47%. Given their coinciding nature with the business cycle, these variables serve to confirm recessions rather than being leading indicators.

Among *inflation* measures, a positive change of the inflation rate is surprisingly associated with an increase of the recession probability. An explanation for the leading characteristic of inflation could be its ability to indicate an overheating of the economy which, in turn, could trigger monetary tightening by the central bank. This characteristic has been of important in the run up to the GFC. Although results for the 12m change of the HICP are relatively strong with an AUROC of 0.82, the variable is vulnerable to policy changes of the inflation target and structurally subdued inflation dynamics [see Table A1].

Within the *commodities* section, findings reveal that an increase in the oil price is associated with an increasing likelihood of recession [see Figure 1g and Table A1]. Although the oil price provides strong summary statistics with an AUROC of 0.82 and 62% of all crisis detected, the recent two years have proven that idiosyncratic supply side dynamics can severely taint the variable's informational content on the endogenous business cycle. For risk-averse investors, the variable ranks 6<sup>th</sup> while risk-affine investors find less utility placing the input factor 41<sup>st</sup> given the highest number of false recession signals among all variables (15%). This underlines the need to analyze underlying drivers of this variable despite sound overall statistical results.

Representing the *wealth channel*, both building permits (6m change) and the EuroStoxx50 (12m change) [see Figure 1h and Table A1] do not qualify as reliable indicators given low AUROCs of 0.76 and 0.69 and only 40% and 16% of recession months detected. Building permits merely capture the first recession given the strong credit expansion in the

---

<sup>21</sup> Main drivers of the EUR/USD FX Basis are identified as reverse Yankee bond issuance and EU investors looking for higher yields in the U.S. (Borio et al. (2016)).

<sup>22</sup> Among the total of all 110 transformations tested, this category (level specification) ranks 38<sup>th</sup> for risk-averse investors and only 55<sup>th</sup> for risk-affine investors.

run-up to the GFC and the related overheating of the housing market but fail to reflect the second economic downturn in the euro area. Detractors of the predictive power of stock market returns are numerous significant price corrections. As most of them were not followed by recessions, the probit model adjusts by showing a lower overall magnitude of swings in recession probability, crossing the 50% threshold only during the sell-off in 2002 and the GFC. Hence, risk-affine investors should not be advised to consider these variables as indicators for economic downturns given aforementioned fluctuations in valuations metrics.<sup>23</sup>

## **2.5 Results of the Submodels**

### ***2.5.1 Submodel 1 – Monetary Transmission Channels***

This submodel extracts the first principal component for categories representing different monetary transmission channels.<sup>24</sup> The idea behind this approach is not necessarily to outperform the results of the benchmark model, but rather finding a specification that removes idiosyncratic vulnerabilities of single indicators. We construct eight monetary transmission channels: Money supply, competitiveness, sentiment, refinancing, preference for risk, industrial data, inflation and commodities.<sup>25</sup> Input factors are chosen based on a reasonable predictive quality in the previous univariate analysis. To ensure comparability among the different channels, we use all input factors in standardized form and with an intended lead-time of 12 months.<sup>26</sup>

The analysis yields the strongest improvements for following groups: Preference for risk, industrial data, and refinancing variables. All three categories are composed of variables that are sensitive to the economic cycle, but at the same time prone to idiosyncratic factors. By extracting the first principal component, it is possible to reduce these non-systemic fluctuations and extract the common driver of variability in the dataset.

---

<sup>23</sup> The average results for the variables reflecting the wealth channel rank 63<sup>rd</sup> for risk-affine investors and 47<sup>th</sup> for risk-averse agents.

<sup>24</sup> For the detailed results of the submodels with respect to our employed information criteria see again the respective tables, while the subsequent figures only highlight the best performing indicators with respect to their probabilities of predicting a recession.

<sup>25</sup> We exclude interest rates, the term spread and a potential wealth channel given the lack of adequate input factors.

<sup>26</sup> Models consisting of more than two factors are established via principal component analysis, which requires standardization of the input factors.

## Figure 2: Submodel 1 - Monetary Transmission Channels

Figure 2a

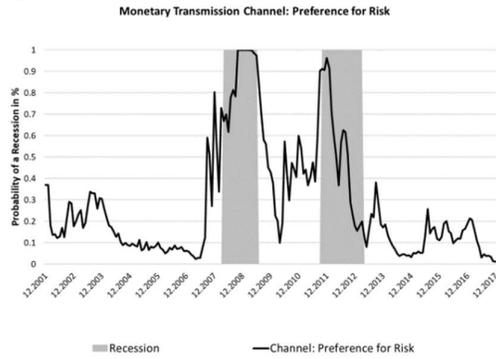


Figure 2b

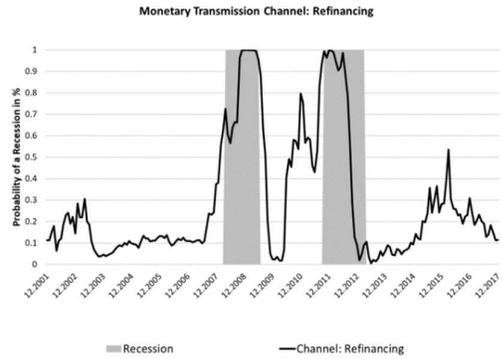


Figure 2c

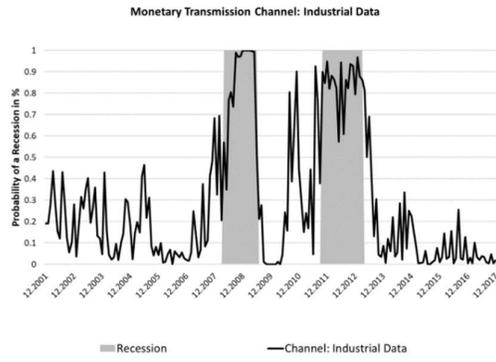


Figure 2d

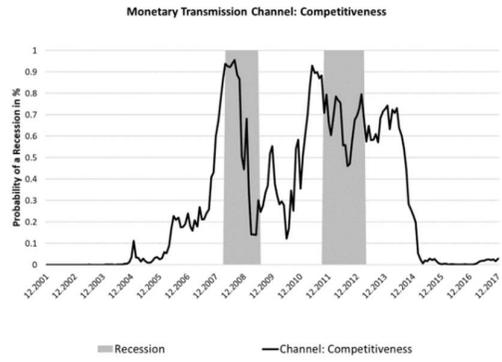


Figure 2e

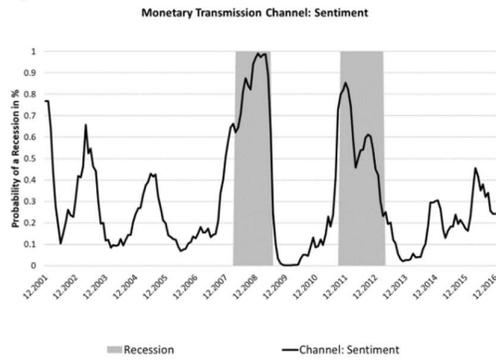


Figure 2f

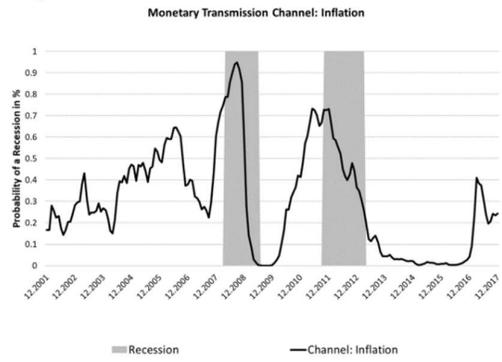


Figure 2g

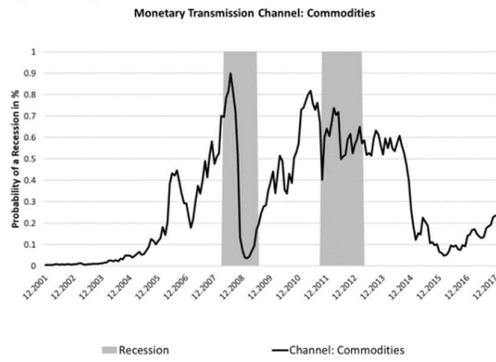
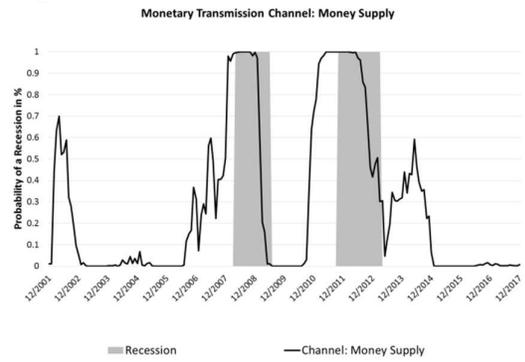


Figure 2h



**Table A2: Submodel 1 - Monetary Transmission Channels**

12m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession		True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C )	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued / No Signal Issued	A / C	B / D					L = 0.25	L = 0.75
<b>Channel: Money Supply</b>				<b>96%</b>	<b>90%</b>	<b>76%</b>	<b>5%</b>	<b>0.09</b>	<b>0.19</b>
Real M1 (12m_ret)				95%	88%	73%	5%	0.10	0.22
<b>Channel: Competitiveness</b>				<b>89%</b>	<b>80%</b>	<b>71%</b>	<b>16%</b>	<b>0.19</b>	<b>0.26</b>
FX EUR/USD				84%	78%	49%	10%	0.20	0.41
Terms of Trade				85%	78%	60%	13%	0.20	0.33
<b>Channel: Sentiment</b>				<b>80%</b>	<b>83%</b>	<b>56%</b>	<b>6%</b>	<b>0.15</b>	<b>0.34</b>
PMI (12m_diff)				88%	83%	60%	7%	0.15	0.32
Economic Sentiment (6m_diff)				82%	82%	56%	6%	0.16	0.34
Industrial Confidence (6m_diff)				81%	82%	51%	5%	0.16	0.38
Business Climate (6m_diff)				81%	82%	51%	5%	0.16	0.38
Consumer Economic Situation (12m_diff)				79%	80%	51%	8%	0.18	0.39
Consumer Confidence (6m_diff)				77%	81%	51%	6%	0.16	0.38
<b>Channel: Refinancing</b>				<b>88%</b>	<b>87%</b>	<b>69%</b>	<b>5%</b>	<b>0.11</b>	<b>0.24</b>
Corporate Bonds: Investment Grade Spread				85%	82%	56%	7%	0.16	0.35
EZ Peripheral Bond Spread (12m_diff)				85%	82%	49%	3%	0.15	0.39
High Yield Spread (12m_diff)				76%	85%	55%	2%	0.13	0.35
<b>Channel: Preference for Risk</b>				<b>86%</b>	<b>85%</b>	<b>62%</b>	<b>5%</b>	<b>0.13</b>	<b>0.30</b>
LiborOIS				82%	82%	53%	6%	0.16	0.37
Implied Rates Volatility				79%	80%	51%	8%	0.18	0.39
FX Basis EUR/USD				78%	75%	38%	9%	0.22	0.49
<b>Channel: Industrial Data</b>				<b>89%</b>	<b>86%</b>	<b>65%</b>	<b>5%</b>	<b>0.12</b>	<b>0.27</b>
Retail Sales (6m_ret)				83%	80%	45%	6%	0.18	0.42
MHG Stocks of Finished Products (6m_diff)				79%	78%	47%	8%	0.19	0.42
New Passenger Cars (12m_ret)				78%	77%	45%	10%	0.21	0.43
<b>Channel: Inflation</b>				<b>84%</b>	<b>80%</b>	<b>53%</b>	<b>8%</b>	<b>0.18</b>	<b>0.37</b>
HICP (12m_ret)				82%	83%	53%	3%	0.14	0.36
Domestic PPI: Industry excluding Construction (12m_ret)				80%	76%	51%	13%	0.22	0.40
<b>Channel: Commodities</b>				<b>85%</b>	<b>80%</b>	<b>71%</b>	<b>16%</b>	<b>0.19</b>	<b>0.26</b>
Crude Oil				82%	78%	62%	15%	0.21	0.32
Gold				76%	82%	49%	3%	0.15	0.39

Regarding preference for risk [see Figure 2a and Table 2A], the channel achieves an AUROC of 0.86 versus an average of 0.80 for its subcomponents. This finding is supported by a surge in accurately called recessions from an average of 47% to 62% and a fall in the number of false positive signals to 5% (average of 7%). Since both the Libor-OIS spread and the FX Basis have shown its vulnerability to exogenous shocks that do not stem from the economic cycle, the signals of the monetary transmission channels prove to be more robust.

The study finds similar results for the refinancing channel with an improvement of the AUROC by 6 percentage points to 0.88 versus the average of its subcomponents which are exposed to risks from European fragmentation and the HY market structure [see Figure 2b and Table 2A]. We find that particularly risk-averse investors benefit from this submodel as the percentage of crisis detected increases to 69% from 53%. This result underlines the strength of the conceptual approach: While the HY and IG corporate bond spreads compensate for the failure of the euro area peripheral sovereign bond indicator during the first recession, the sustained positive recession signals of the latter in the run-up the second economic downturn is improving the channel’s performance compared to the corporate spread variables.

Along the same lines, the channel of industrial variables indicates an improvement of the AUROC from an average of 0.80 to 0.89 of the combined model [see Figure 2c and Table A2]. While new passenger cars and stocks of finished products do not serve as solid single indicators given a high number of false positive signals (average of 9%) and mediocre amount of crisis detected (average 46%), their combination with retails sales drives up the number of correctly predicted recessions to 65% and lowers the amount of false positive signals to 5%.

Hence, even relatively volatile input factors can provide predictive value by their inclusion into existing models.

Regarding the competitiveness channel, we find a strong increase in accurately predicted recession months up to 71% from an average of 55% for the subcomponents [see Figure 2d and Table A2]. The other monetary transmission channels (inflation, commodities, sentiment) yield results which are broadly in line with their underlying subcomponents. To provide insights into how much of the results is owed to the standardization of the variables, we included one model, labelled *money supply*, which includes only one standardized time series (real M1). The results reveal that there is no material change as the AUROC improves marginally by 1pp [see Table A2].

To conclude, the modeling of monetary transmission channels via principal component analysis yields significantly better results, in particular, for those channels whose subcomponents are most affected by idiosyncratic exogenous shocks. Besides statistical evidence, there is also a conceptual perspective that suggests higher future robustness associated with the use of aggregated channels even if results are in line with the underlying single input factors.

### ***2.5.2 Submodel 2 – Bivariate Specification***

The second modification estimates bivariate probit regressions based on the six best single indicators from the benchmark model [see Figure 3 and Table A3 for the results]. To ensure that the selected variables are not close substitutes but complementary in nature, this section first identifies the leading indicators of the different categories and then considers the six best-performing variables in all possible combinations. The chosen indicators are: Real M1 (12m change), PMI (12m change), IG corporate bond spread (level), Terms of Trade (level), retail sales (6m change) and the oil price (level). In a second step, we conduct a similar exercise for the monetary transmission channels that cover the following six variables: Money supply, sentiment, refinancing, competitiveness, industrial data, and commodities.

The results of the bivariate probit models improve the AUROC on average by 0.06 percentage points (pp) to 0.93 vis-à-vis the average performance of the single underlying indicators. The stronger performance is reflected in a surge of crisis detected by 17pp to 0.76 and a reduction of false signals by 2pp to 0.09.

### Figure 3: Submodel 2 - Bivariate Specification

Figure 3a

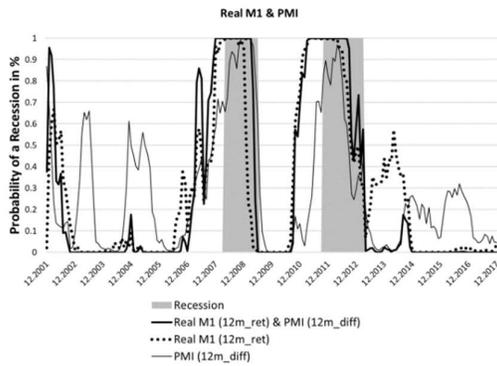


Figure 3b

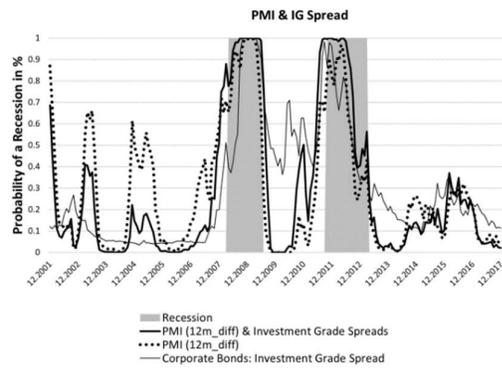


Figure 3c

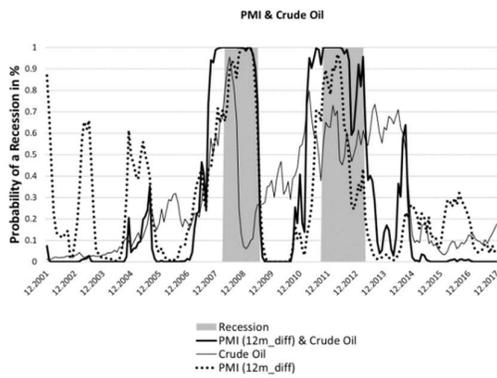


Figure 3d

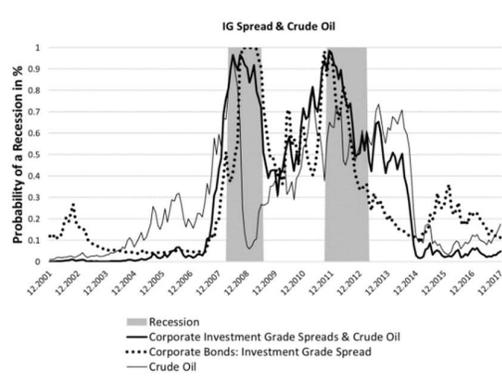


Figure 3e

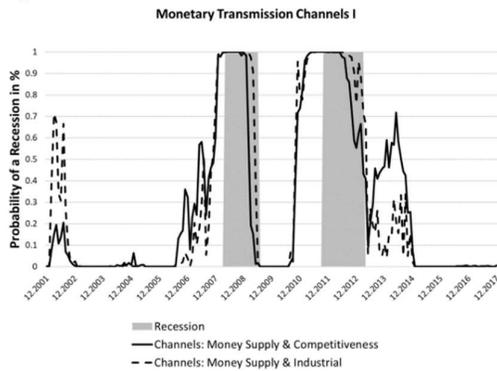


Figure 3f

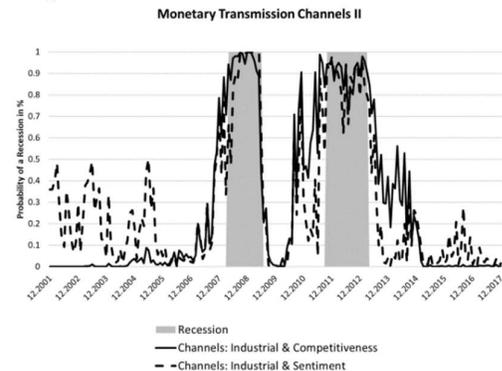


Figure 3g

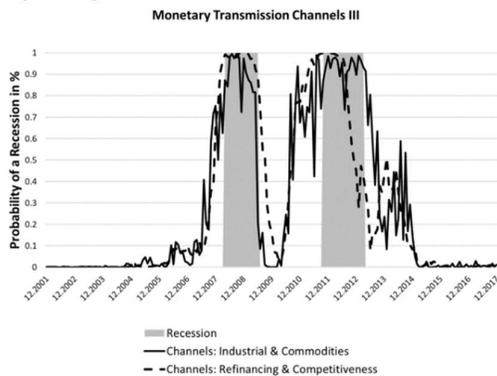
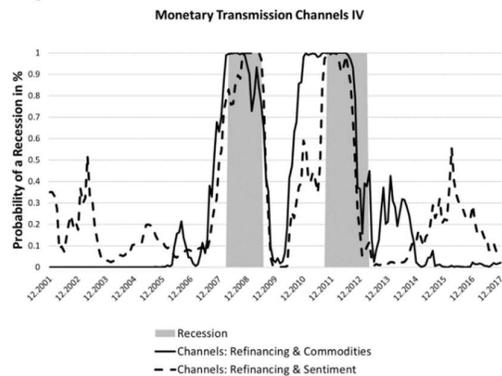


Figure 3h



**Table A3: Submodel 2 - Bivariate Specification**

12m Forecasting Horizon			AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse	
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued	A	B					L= 0.25	L= 0.75
	No Signal Issued	C	D						
Single Indicators	Real M1 (12m_ret) & PMI (12m_diff)			99%	95%	91%	3%	0.05	0.08
	Real M1 (12m_ret) & Investment Grade Spreads			97%	93%	82%	2%	0.06	0.14
	Real M1 (12m_ret) & Terms of Trade			96%	91%	78%	4%	0.08	0.17
	Real M1 (12m_ret) & Retail Sales (6m_ret)			97%	93%	89%	5%	0.06	0.09
	Real M1 (12m_ret) & Crude Oil			96%	91%	76%	2%	0.08	0.18
	PMI (12m_diff) & Investment Grade Spreads			93%	87%	64%	3%	0.11	0.28
	PMI (12m_diff) & Terms of Trade			97%	91%	78%	3%	0.08	0.17
	PMI (12m_diff) & Retail Sales (6m_ret)			90%	85%	71%	9%	0.14	0.24
	PMI (12m_diff) & Crude Oil			98%	92%	82%	4%	0.08	0.15
	Corporate Investment Grade Spreads & Terms of Trade			90%	86%	78%	11%	0.14	0.19
	Corporate Investment Grade Spreads & Retail Sales (6m_ret)			87%	83%	62%	7%	0.15	0.30
	Corporate Investment Grade Spreads & Crude Oil			93%	86%	76%	10%	0.13	0.20
	Terms of Trade & Retail Sales (6m_ret)			90%	86%	78%	10%	0.13	0.19
	Terms of Trade & Crude Oil			86%	79%	65%	15%	0.20	0.30
	Retail Sales (6m_ret) & Crude Oil			89%	84%	75%	12%	0.15	0.22
	Channels: Money Supply & Industrial			98%	93%	87%	4%	0.06	0.11
	Channels: Money Supply & Refinancing			98%	94%	87%	3%	0.06	0.10
	Channels: Money Supply & Competitiveness			97%	91%	82%	5%	0.08	0.15
	Channels: Money Supply & Sentiment			98%	94%	87%	3%	0.06	0.10
	Channels: Money Supply & Commodities			97%	92%	82%	3%	0.07	0.14
Channels: Industrial & Refinancing			93%	88%	73%	6%	0.11	0.22	
Channels: Industrial & Competitiveness			96%	90%	82%	7%	0.10	0.15	
Channels: Industrial & Sentiment			90%	87%	69%	5%	0.11	0.24	
Channels: Industrial & Commodities			96%	91%	87%	7%	0.09	0.11	
Channels: Refinancing & Competitiveness			96%	91%	78%	4%	0.08	0.17	
Channels: Refinancing & Sentiment			89%	86%	62%	3%	0.12	0.29	
Channels: Refinancing & Commodities			97%	92%	82%	3%	0.07	0.14	
Channels: Competitiveness & Sentiment			97%	91%	78%	4%	0.08	0.17	
Channels: Competitiveness & Commodities			90%	81%	73%	16%	0.19	0.24	
Channels: Sentiment & Commodities			98%	91%	84%	6%	0.09	0.14	

The supreme combination is Real M1 and the PMI which reaches a near-perfect AUROC of 0.99 with 95% correct signals and 91% of crisis detected (missing only five recession months) [see Figure 3a and Table A3]. All other combinations that include Real M1 or the PMI perform marginally worse but still significantly better than the single input factors. Beneficial for the combination of Real M1 and the PMI is the leading nature of Real M1 in the run-up to the first recession, whereas the PMI remains elevated somewhat longer during the recession. This combination of complementary characteristics enables the bivariate model to improve the lead-time and cover the length of the economic downturn more accurately. Besides the paramount performance of bivariate models that include either Real M1 or the PMI, the combination of IG corporate bond spreads and crude oil leads the ranking of other potential pairs closely followed by the pair of Terms of Trade and retail sales.

Results for the monetary transmission channels underline the findings for the single input factors. As the concept of transmission channels introduces a greater variety of variables, we find this procedure to be balancing the superior statistical performance of bivariate analysis while reducing the inherent risk of overfitting.

**2.5.3 Submodel 3 – Unstable Surge**

The third modification introduces the relative state of a variable versus its long-term trend in order to identify what Keynes termed “Animal Spirits” as well as potential hawkish mistakes by the central bank [see Figure 4 and Table A4 for the results].

**Figure 4: Submodel 3 - Unstable Surges**

Figure 4a

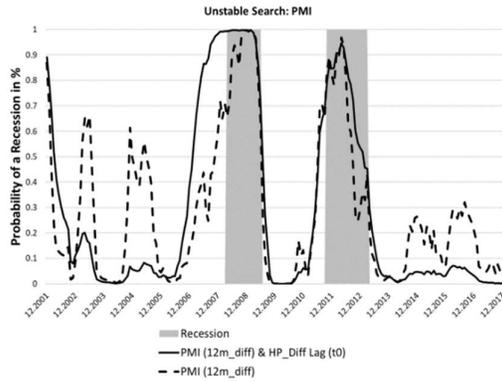


Figure 4c

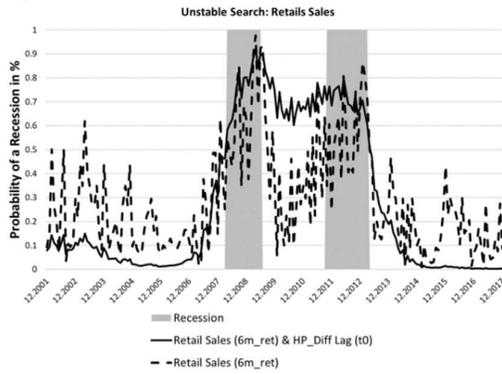


Figure 4e

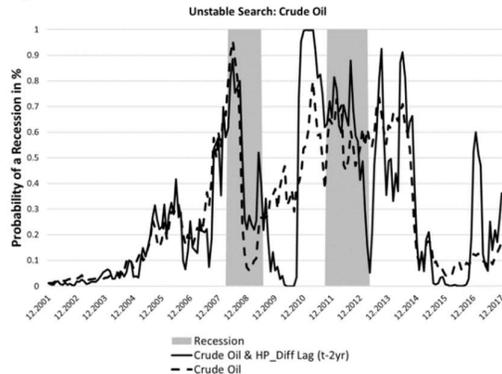


Figure 4g

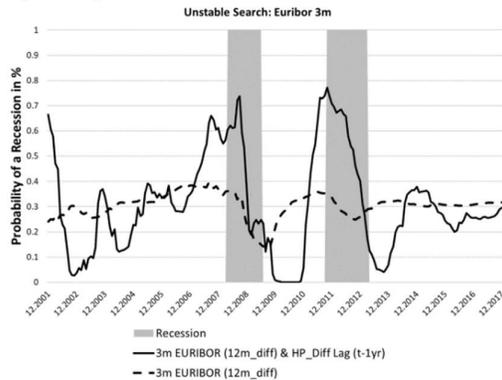


Figure 4b

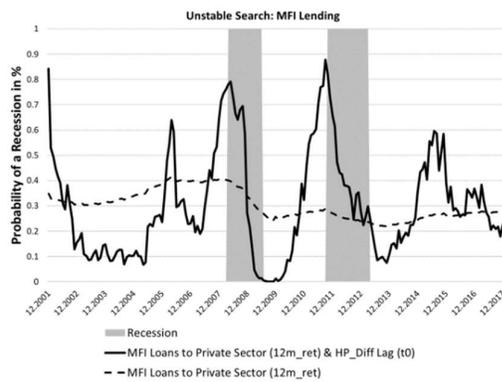


Figure 4d

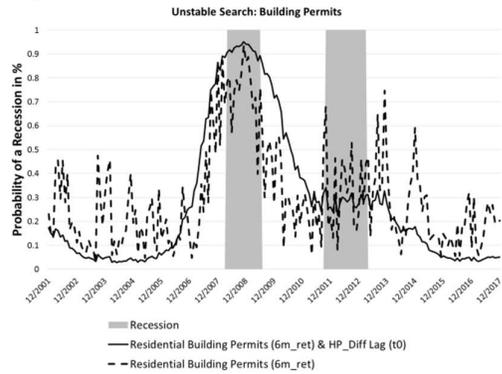


Figure 4f

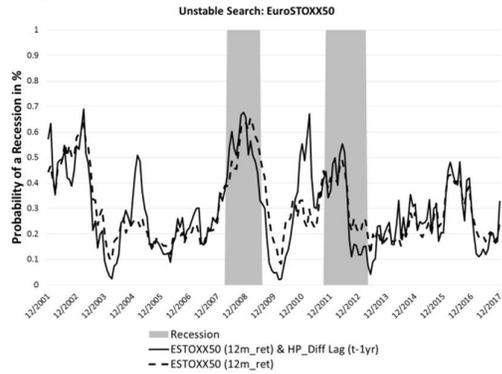
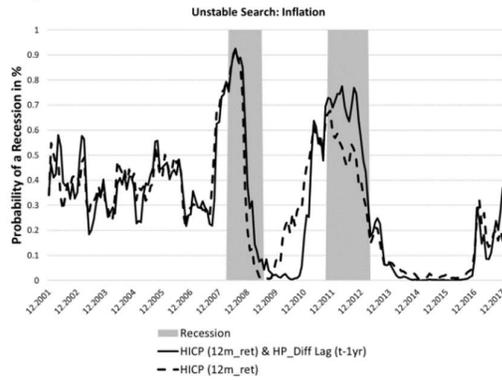


Figure 4h



**Table A4: Submodel 3 - Unstable Surges**

12m Forecasting Horizon			AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse	
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C )	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued	A	B					L = 0.25	L = 0.75
	No Signal Issued	C	D						
Money Supply	<b>Real M1 &amp; HP Diff Lag (t0)</b>			97%	90%	80%	6%	0.09	0.16
	Real M1 & HP Diff Lag (t-1yr)			97%	92%	84%	5%	0.08	0.13
	Real M1 & HP Diff Lag (t-2yr)			96%	90%	78%	5%	0.09	0.18
	Single Indicator: Real M1 (12m ret)			95%	88%	73%	5%	0.10	0.22
Equity Markets	ESTOXX50 (12m ret) & HP Diff Lag (t0)			68%	70%	18%	7%	0.26	0.63
	<b>ESTOXX50 (12m ret) &amp; HP Diff Lag (t-1yr)</b>			71%	75%	33%	7%	0.22	0.52
	ESTOXX50 (12m ret) & HP Diff Lag (t-2yr)			69%	69%	16%	9%	0.27	0.65
Building Permits	ESTOXX50 (12m ret)			69%	68%	16%	10%	0.28	0.65
	<b>Residential Building Permits (6m ret) &amp; HP Diff Lag (t0)</b>			89%	76%	45%	11%	0.22	0.44
	Residential Building Permits (6m ret) & HP Diff Lag (t-1yr)			81%	81%	53%	6%	0.17	0.37
	Residential Building Permits (6m ret) & HP Diff Lag (t-2yr)			76%	77%	40%	6%	0.20	0.47
Sentiment	Residential Building Permits (6m ret)			76%	77%	40%	6%	0.20	0.47
	<b>PMI (12m diff) &amp; HP Diff Lag (t0)</b>			94%	91%	82%	6%	0.09	0.15
	PMI (12m diff) & HP Diff Lag (t-1yr)			90%	81%	62%	11%	0.18	0.31
	PMI (12m diff) & HP Diff Lag (t-2yr)			90%	82%	64%	10%	0.17	0.30
Inflation	Single Indicator: PMI (12m diff)			88%	83%	60%	7%	0.15	0.32
	<b>HICP (12m ret) &amp; HP Diff Lag (t0)</b>			82%	85%	55%	2%	0.13	0.35
	HICP (12m ret) & HP Diff Lag (t-1yr)			84%	85%	62%	5%	0.13	0.30
	HICP (12m ret) & HP Diff Lag (t-2yr)			84%	82%	56%	6%	0.16	0.34
Retail	Single Indicator: HICP (12m ret)			82%	83%	53%	3%	0.14	0.36
	<b>Retail Sales (6m ret) &amp; HP Diff Lag (t0)</b>			90%	83%	78%	14%	0.16	0.20
	Retail Sales (6m ret) & HP Diff Lag (t-1yr)			85%	79%	51%	9%	0.19	0.39
	Retail Sales (6m ret) & HP Diff Lag (t-2yr)			83%	79%	44%	6%	0.18	0.44
Credit Dynamics	Single Indicator: Retail Sales (6m ret)			83%	80%	45%	6%	0.18	0.42
	<b>MFI Loans to Private Sector (12m ret) &amp; HP Diff Lag (t0)</b>			81%	78%	47%	9%	0.20	0.42
	MFI Loans to Private Sector (12m ret) & HP Diff Lag (t-1yr)			70%	70%	4%	1%	0.25	0.72
	MFI Loans to Private Sector (12m ret) & HP Diff Lag (t-2yr)			62%	72%	9%	1%	0.23	0.68
Oil	Single Indicator: MFI Loans to Private Sector (12m ret)			58%	70%	0%	0%	0.25	0.75
	<b>Crude Oil &amp; HP Diff Lag (t0)</b>			88%	76%	53%	13%	0.22	0.39
	Crude Oil & HP Diff Lag (t-1yr)			84%	76%	56%	16%	0.23	0.37
	Crude Oil & HP Diff Lag (t-2yr)			90%	85%	71%	9%	0.14	0.24
Central Bank Policy	Single Indicator: Crude Oil			82%	78%	62%	15%	0.21	0.32
	<b>3m EURIBOR (12m diff) &amp; HP Diff Lag (t0)</b>			63%	70%	0%	0%	0.25	0.75
	3m EURIBOR (12m diff) & HP Diff Lag (t-1yr)			86%	88%	65%	2%	0.10	0.27
	3m EURIBOR (12m diff) & HP Diff Lag (t-2yr)			57%	75%	16%	0%	0.21	0.63
	Single Indicator: 3m EURIBOR			64%	80%	33%	0%	0.17	0.50

Traditional probit models tend to signal an elevated likelihood of a recession when indicators are deteriorating. However, the build-up of unsustainable momentum of economic developments can be an early indicator of a looming correction following the possible collapse of over-optimism and inadequate production planning. Likewise, a hiking cycle which is too aggressive might be the harbinger of monetary tightening that has the potential to cause an economic downturn.

Hence, the idea is to detect periods of unstable surges measured against the Hodrick-Prescott (HP) trend estimated with a parameter value  $\lambda$  of 14,400 given the underlying monthly time series. The actual bivariate model consists of two input factors: 1) An indicator that we suspect to be reflective of unstable business cycle dynamics 2) the deviation of this time series from its HP trend with three different lag structures (contemporaneous, with a 12m lag or a 24m lag). Potential indicators representing an overheating of the economy driven by animal spirits are: EuroStoxx50 (12m change), building permits (6m change), PMI (12m change), retail sales (6m change), monetary financial institution (MFI) loans to the private sector (12m change) and crude oil (level). Input factors that are tested for their ability to detect a tightening of central bank policy are: Euribor (12m change), money supply (12m change) and inflation (12m change). Among the variables tested, results for the PMI (contemporaneous version) yield a surge in the number of recession months detected by 22pp up to 82% [see Figure 4a and Table A4]. The lead-time towards the first recession rises from five months to 14 months while there is no improvement for the second recession as the

economic downturn starting in 2011 was not preceded by an overly optimistic outlook of producers.

Notwithstanding the fact that growth of MFI loans does not detect a single recession month in the baseline model, the augmentation incorporating the HP deviation (contemporaneous version) yields an AUROC of 0.81 and correctly identifies 47% of all crisis periods [Figure 4b and Table A4]. In addition, this transformation shows a remarkable lead-time of six months before the GFC and eight months before the second recession. Findings for retail sales (contemporaneous version) indicate particular appeal for risk-averse investors whose utility rises significantly [Figure 4c and Table A4]. While the AUROC increases by 0.07 to 0.90, the number of detected crisis almost doubles from 45% to 78%. The flipside of these results is a higher number of false positive signals of 14% (up from 6%) which could be too noisy for risk-affine agents.

Results for building permits underline the strength and the incompleteness of this variable [Figure 4d and Table A4]. Statistics point to a strong improvement of the AUROC to 0.89 up from 0.76. However, this is mainly due to a more accurate reflection of animal spirits in the run-up to the first recession. Given the lack of causality, the augmented indicator also misses out completely on the second economic downturn. Results for the other indicators do not show improved test statistics as both EuroStoxx50 and crude oil remain volatile, while the indicator of retail sales does not recede in between the two recessions

With regard to hawkish mistakes by the central bank, we find that the augmented variable of the 3m Euribor carries predictive value [Figure 4g and Table A4]. While the indicator does not call any recession month in the univariate benchmark model, the modification including a one-year lag results in an AUROC of 0.86 and 65% of recession months detected. The augmentation captures both recessions with a lead-time of ten months (first recession) and six months (second recession), indicating that an above-trend increase of the Euribor might signal the central bank's attempt to tighten monetary supply. In particular, the two hikes in the run-up to the second recession represent a poster model for a hawkish mistake. On the inflation variable, results suggest that a positive deviation from trend increases the probability of a recession [Figure 4h and Table A4]. As above-trend inflation could induce a central bank to tighten rates, this indicator yields a moderate increase of recessions detected to 62% (up from 53%). Results for money supply are broadly in line with the univariate benchmark analysis with an AUROC inching slightly higher to 0.97 (up from 0.95).

To conclude, the addition of the deviation of indicators from their HP trend yields significant improvements for some of the variables as they are potential witnesses to unsustainable surges. Nevertheless, the results need to be interpreted with some caution as the HP trend is quite sensitive to the latest values of a time series and the ex-post analysis does not replicate a real-time assessment.

## **2.6 Out-of-Sample Analysis and Varying Time Horizons**

### ***2.6.1 Out-of-Sample Analysis***

The out-of-sample test is calibrated for the time period between December 2001 and August 2010. Hence, it covers the period leading up to the GFC, the full length of the first recession and 14 months of the subsequent expansion phase, leaving a buffer of 13 months until the start of the second recession. The detailed results for the benchmark model are displayed in Table A5 in the Appendix, while Tables A6 through A8 in the Appendix show the result of the out-of-sample analysis for the three submodels.

Regarding the univariate benchmark model, the analysis allows a broad classification into two groups of indicators: Those variables that are rather unspecific in nature and a reflection of broader business cycle dynamics as well as those indicators that are specific to the respective recession. Indicators that display the ability to capture both recessions are Real M1, the PMI, retail sales, implied interest rate volatility, the Libor-OIS spread, and crude oil whose summary statistics are similar to those of the benchmark model from section 2.4. Variables falling short of predicting both economic downturns are the term spread, the euro area peripheral sovereign bond spread, inflation and building permits. In particular the euro area peripheral sovereign bond spread underlines the necessity to consider potential structural breaks: While investors have assumed an implicit guarantee of euro area government debt by other members of the currency bloc before the European debt crisis, the indicator has become informative only after markets have revised this assumption in light of redenomination risks. On the same note, the potential formation of a European Monetary Fund, as currently discussed by policymakers, could represent a development that decreases the predictive quality of the indicator given lower sensitivity of spread levels.

### ***2.6.2 The Benchmark Model over Various Time Horizons***

To introduce an additional dimension, the analysis modifies the forecasting horizon to 6m, 18m and 24m to shed further light on the leading, coinciding or lagging nature of potential indicators.

For the 6m forecasting horizon, both industrial data and sentiment indicators gain substantially in predictive quality [see Table A9 in the Appendix for the details]. The PMI (12m change) becomes the best performing indicator with an AUROC of 0.95 (+0.07)<sup>27</sup> and 74% of crisis detected (+14pp). This result is reflective for the broader group of sentiment variables whose AUROCs increase to an average of 0.86 (up from 0.73). With regard to the category of industrial variables, we find very strong performance of retail sales (6m change) and stocks of finished products (12m change) whose AUROCs increase to 0.90 (+0.07) and 0.89 (+0.12) respectively on the back of better crisis detection and less false positive signals. Findings for both categories emphasize their particular usefulness in validating recessions given their shorter lead-time. Both buildings permits and the EuroSTOXX50 improve their results for the 6m horizon but still clearly underperform other indicators. For the other categories, we find a tendency of fewer crises detected and less false signals. As a consequence, models covering shorter time horizons provide a valuable perspective for risk-affine investors who face higher costs of false positive signals.

For the 18m horizon [see Table A10 in the Appendix], sentiment indicators and industrial data deteriorate across the board and lose out on their predictive capabilities, while financial market spread indicators closely track Real M1 as the best performing variables due to their longer-lead time. As to the forecasting ability of Real M1, the percentage of crisis detected remains practically unchanged at 75% versus the benchmark model, but false positive signals increase by 10pp to 15%. A common observation for the 18m forecasting horizon is a higher number of false positive signals which raises particularly the costs for the risk-affine investor type.

Considering the 24m forecasting horizon, findings indicate that it is hardly possible to achieve reliable forecasting performance [see Table A11 in the Appendix]. In particular, the number of false alarm surges across the dataset, declaring on average 18% of all expansion months to recessions (versus 3% for the 12 month forecasting horizon). Only two variables stand out with a slight deterioration against the 18m horizon: Both the peripheral sovereign spread and the IG corporate bond spread yield only moderately weaker results and could serve risk-averse investors as early warning indicators with a considerable lead-time.

### ***2.6.3 Submodels over Various Time Horizons***

Considering the first submodel, results indicate superior performance of the monetary transmission channels incorporating industrial data, sentiment variables and money supply

---

<sup>27</sup> The number in brackets indicates the relative change to the results of the 12m forecasting horizon.

with AUROCs between 0.95 and 0.93 and 72% to 70% of recession months correctly called<sup>28</sup> [see Table A12 in the Appendix for all time horizons]. Looking at the extended forecasting periods of 18 to 24 months, we note for sentiment variables an expected decrease in their predictive abilities (AUROC of 0.69), whereas refinancing variables perform reasonably well with an AUROC of 0.83 and 66% of recessions detected. Surprisingly good predictive qualities for the longer term horizon are associated with the channel capturing the preference for risk. In particular risk-affine investors will benefit from only 12% false positive signals (versus 23% of the other channels).

Based on bivariate specifications, the second submodel continues to yield significantly better results than their underlying univariate time series [Table A13 in the Appendix]. With an average AUROC of 0.98 and 82% of crisis months detected across all possible combinations, the PMI and Real M1 are the preferred indicators for the 6m horizon. In light of their shorter lead-time, channels composed of industrial data and sentiment variables display very strong predictive ability. Lengthening the time horizon to 18 months reveals a substantial increase in the number of false positive signals, whereas monetary transmission channels perform better than their univariate peers with 11% false alarm versus 14%.<sup>29</sup> A reason for the higher stability of monetary transmission channels could be the inclusion of variables that are not perfectly congruent in their lead-time.

Regarding the third submodel of unstable surges, the analysis reveals for the 6m horizon an AUROC of 1 for Real M1 with 93% of all recessions months correctly identified [see Table A14 in the Appendix]. Even for the 18m horizons, this augmentation detects 79% of all crises while issuing 15% false positive signals. Both retail sales and MFI loans prove robust for the shorter term horizon with an AUROC of 0.94 (0.90 in the baseline model) and 0.82 respectively (0.81 in the baseline model). The further we move out on the forecasting horizon, the more important becomes the calibration of the lag structure. In light of the results for the 18m horizon, we suggest a coinciding assessment of the cyclical stance (contemporaneous lag) as compared to a lag of 12 months or 24 months for the shorter-term forecasting horizons. Contrary to previous results that render retail sales rather useless for the longer term perspective, the third submodel yields an AUROC of 0.88 and 80% of crisis detected for retail sales over the 24m horizon.

---

<sup>28</sup> While preference for risk and the competitiveness channel yield overall strong results, they are lagging either with regard to the number of recession detected (60% for preference of risk) or a higher number of false alarm (8% for competitiveness).

<sup>29</sup> The average number of crisis detected is similar with 73% for channels versus 72% for univariate indicators.

## 2.7 Concluding Remarks on Recession Probabilities

In order to assess recession probabilities for the euro area, this paper applied four different approaches: A univariate benchmark model to identify predictors and their preferred transformations as well as three submodels. For all four approaches, out-of-sample analyses are performed as well. To increase robustness and to capture additional dynamics, various forecast horizons next to the benchmark of 12 months were employed to validate the lead-time. In order to measure the predictive power of the indicator variables we rely on three different signaling approaches to come up with robust results: A signaling approach (Kaminsky and Reinhart (1999)), the area under the receiver operating curve (AUROC) and a loss function to model risk-averse and risk-seeking investors (Alessi and Detken (2009)).

The regime change of monetary policy at the zero lower bound is posing challenges to the empirical supremacy of the term spread for signaling recessions. We find that a modified version of the yield curve incorporating the shadow rate by Xia and Wu (2016) removes the downward rigidity of the front-leg and restores part of the informational content of the yield curve. However, regarding the 12m forecasting horizon, the best performing single indicator of the analysis is Real M1 with a lead-time of eleven months before the start of both recessions under consideration. Slightly trailing in performance, the PMI, the IG corporate bond spread and Terms of Trade yield the highest predictive quality. Considering the 12m transformation of variables instead of their level increases the sensitivity vis-à-vis turning points of the business cycle for those variables that are less leading in nature. Other variables (e.g. Libor-OIS, crude oil) generate good summary statistics but reveal idiosyncratic vulnerabilities that can lead to a higher number of false positive signals.

For risk-averse investors, who are more concerned with detecting a crisis at the expense of a higher number of false positive signals, there is higher relative utility in considering the price of crude oil and Terms of Trade. Results for risk-affine investors suggest a higher relative reliance on variables that are producing fewer false alarms such as HICP inflation and the euro area peripheral sovereign bond spread.

On the first submodel, the creation of monetary transmission channels yields the strongest improvements for the categories of industrial data, refinancing variables and preference for risk. As all those three categories are composed of variables prone to idiosyncratic fluctuations, the use of principal component analysis increases the informational value regarding the business cycle. Results for the second submodel suggest bivariate combinations perform significantly better than the univariate specification. In particular, combinations of indicators including Real M1 or the PMI can be considered to be paramount.

Bivariate models of monetary transmission channels also outperform their univariate equivalents by far and, in addition, reduce the risk of overfitting compared to bivariate models of single indicators. Considering the deviation from the HP trend in the third submodel achieves significant improvements for indicators in the run-up to the recession of 2008-2009 which can be characterized by signs of overheating. Similarly, monetary policy variables become more sensitive through suggested modification by capturing potential hawkish mistakes.

Regarding different forecasting horizons, sentiment indicators and industrial data improve significantly for shorter time horizons, whereas corporate spreads and the euro area peripheral sovereign bond spread underline their leading character vis-à-vis the business cycle given a remarkable performance over a longer forecasting horizon. Most of the indicators fail to be useful over the 24m horizon given a high number of false signals. However, indicators of the third submodel reflecting unstable surges provide moderately robust results also for extended forecasting horizons that could serve as complements to short-term forecasts.

### 3. The Shape of Euro Area's Uncertainty: Its Impact and Predictive Value on GDP<sup>30</sup>

The purpose of this chapter is to shed light on the role of uncertainty in the context of business cycle dynamics in the Euro area. There is consensus in the literature that uncertainty among economic agents has a measurable effect on real economic variables. However, researchers seem to be divided on the question of how to define uncertainty, which ultimately determines its measurement and quantification. Concepts of uncertainty range from observable measures such as implied volatilities in financial markets and sentiment indices at the one end of the spectrum to Knightian uncertainty (Knight, 1921) on the other end, aspiring to observe the unobservable. To bridge the gap between these different ideas about uncertainty, this chapter first decomposes uncertainty into different layers along the four moments of the distribution: We define the first moment as the general confidence level that economic agents state in surveys or via implied volatilities in financial markets. The second, third and fourth moment of uncertainty focuses on the shape of the distribution of confidence estimates and implied volatilities in terms of the standard deviation, the skewness and the

---

<sup>30</sup> This chapter is based on: Fendel et al. (2019b): The shape of euro area's uncertainty: Its impact and predictive value on GDP, Unpublished WHU Working Paper Series, No.19-01.

kurtosis. To capture uncertainty holistically for the economy, we consider three groups: consumers, producers and financial market participants. Subsequently, we construct aggregate measures of uncertainty across these agents for the four moments and qualitatively assess their behavior vis-à-vis the business cycle. A second area of interest is the quantitative impact of uncertainty on GDP considering a parsimonious specification of the business cycle in a VAR. The third perspective focuses on the informative value that the different moments of uncertainty provide to GDP forecasts. We subsequently validate results of the third perspective by examining how much of the variation in the second moment of uncertainty is actually driven by the first moment.

This chapter has the following structure. Section 3.1 provides a literature review covering the three economic groups and the four moments of uncertainty. Section 3.2 presents the model set-up and the underlying data of the analysis. Section 3.3 analyzes the shape of uncertainty vis-à-vis the business cycle from a qualitative perspective and continues with a quantitative analysis on the impact of uncertainty on real GDP via impulse response functions. Section 3.4 assesses the informational value of the four moments in the context of their forecasting performance on real GDP. To account for potential endogeneity, this section concludes with an analysis that sheds light on the relationship between the first and the second moment of the distribution. Section 3.5 concludes the chapter with a brief summary.

### **3.1 Literature on Economic Uncertainty**

The relevant sources of uncertainty can be broadly classified into three groups of agents whose activities ultimately affect the real economy. At the very core of these inherently unobservable dynamics are consumers and corporations who determine aggregate demand and supply of the economy. Both economic agents can develop uncertainty for a multiple of reasons related to the current stance of the business cycle. Representing a third group, financial market participants and their lack of confidence can create exogenous shocks on consumers and corporations alike through changes in financial conditions. As the actual interplay between these three economic groups is very nuanced without clear-cut causality, this section sheds light on each representative agent separately. Subsequently, we review findings on the different moments of uncertainty and their informational value regarding the business cycle.

#### ***3.1.1 Consumers***

Households form expectations about several interdependent variables which influence their economic behavior. These expectations cover the macroeconomic perspective (e.g. general

economic situation, price trends) and the individual outlook (e.g. personal financial position, employment status, income situation and major purchases). Increasing uncertainty in these areas affects two transmission channels: the time-varying level and the composition of consumption spending. According to most lifecycle models of consumption, a higher level of uncertainty has long been associated with higher levels of precautionary savings to self-insure through a delay of consumption (Deaton (1991), Caballero (1991)), even though some studies have casted doubts on this causality (Dynan 1993). Christelis et al. (2016) analyze the motives behind changes in savings based on a sample of Dutch households. While previous empirical research has predominantly used ex-post consumption as an input factor into the Euler equation, the authors sidestep potential questions of endogeneity by referring to consumption expectations and can confirm strong precautionary savings in the presence of uncertainty.

The second transmission mechanism of consumer uncertainty is a change in the composition of purchases. However, literature is less conclusive on the proposed causality. Proponents of this channel argue that consumers will delay spending on durables caused by temporary income uncertainty. Romer (1990) notes that during the period of the Great Depression in 1929, consumption of durables has declined while spending on non-durables has increased.<sup>31</sup> Contrary to her findings, research on the post-war era finds a negative relationship between income uncertainty and spending on non-durables based on survey data (Hahm and Steigerwald (1999), Madsen and McAleer (2000)).

### ***3.1.2 Corporations***

The effects of uncertainty surrounding the business outlook of producers are weighing ultimately on the real economy from two different angles: Investments in capital goods and hiring decisions, the later feeding into consumer uncertainty. First, investment spending requires decision makers to assess the confidence level of their forecasts. According to the ‘wait-and-see’ effect, companies could opt to defer an investment decision until an updated set of information increases their confidence. Bernanke (1983) provides theoretical foundation that it is reasonable for companies to defer irreversible investments in the light of uncertainty, if the value of the information gained by waiting exceeds the costs of postponing a decision. In a model of risk-neutral agents in an energy-importing economy, Bernanke shows that uncertainty increases the value of incoming information which increases, in turn, the benefits of waiting. Hence, uncertainty depresses investments in the short-run and contributes to business cycle fluctuations. Pindyck (1991) argues that the ‘wait-and-see’ effect needs

---

<sup>31</sup> Romer (1990) uses stock market volatility as a proxy for uncertainty.

consideration when dealing with the future value of objects, which are inherently difficult to value. A wilderness area, for example, requires an adequate stochastic modeling of its value before starting its economic exploitation. In fact, the option value of waiting should be added as a foregone opportunity expressed as direct costs to the destruction of the wilderness area. Stokey (2016) develops a model of investment decisions where a change in tax policy induces corporations into a ‘wait-and-see mode’. After gaining full insights into the newly introduced fiscal legislation, companies undertake the postponed, irreversible investment projects which lead to a temporary investment boom. While Bachmann et al. (2013) confirm in an SVAR that uncertainty shocks can create protracted negative impulses on economic activity, they emphasize the possibility of a reverse causality. In fact, the authors discuss the idea that uncertainty is not an autonomous source of economic fluctuations, but rather a result of a negative first moment shock in the economy. Their analysis is based on business surveys from the US and Germany covering manufacturing firms<sup>32</sup> by modeling the ex-ante dispersion and the realized forecast errors.

Regarding the second transmission channel, hiring decisions under uncertainty are likely to impact both the demand side, through the purchasing power of consumers, and the supply side of an economy, through the size of production capacity. As turning points of economic cycles are inherently difficult to predict, firms could seek for a fuller set of information before changing the level of their workforce in the presence of inhibiting labor market regulation. Arellano et al. (2011) establish a general equilibrium model that incorporates employment decisions of heterogeneous firms under imperfect financial markets. Firms are facing the trade-off between increasing returns as a function of labour and higher risk of default in case of demand shocks. According to the authors, a higher variance of expected aggregate demand leads to a fall in employment. Along similar lines, Ernst and Viegelahn (2014) develop an indicator reflecting hiring uncertainty among employers. Based on a modified investment model of McDonald and Siegel (1986), the authors determine two labour productivity thresholds at which firms start to hire or lay off workers facing a return and cost trade-off. The authors infer the level of hiring uncertainty based on a function of the actual hiring decisions by firms incorporating the observed labour productivity level within the economy. Results lend support to the hypothesis that labour markets play a crucial transmission mechanism of uncertainty. Despite the general notion in literature to connote uncertainty with a dampening effect, there is theoretical support for the opposite idea that

---

<sup>32</sup> The surveys are the German IFO Business Climate Survey and the Philadelphia Fed’s Business Outlook Survey.

uncertainty can actually increase hiring and investment through growth options and the Oi-Hartman-Abel effect.<sup>33</sup> While the idea of growth options refers to the upside potential of entering new product or regional markets providing a positive skew of potential returns, the Oi-Hartman-Abel effect relies on the assumption that profits are convex in costs and demand. Assuming that firms are able to increase and decrease production on the basis of a new information set, demand or cost uncertainty actually increase potential profits.

### ***3.1.3 Financial Market Participants***

Uncertainty among financial market participants can affect both aggregate supply and demand of the real economy through changes in financial conditions. However, the causality between uncertainty and a change in financial conditions often remains ambiguous: On the one hand, uncertainty can originally emerge within financial markets creating an exogenous shock that leads to a worsening of refinancing conditions and a subsequent slump in investment and consumption. On the other hand, uncertainty could act as an amplification mechanism of the business cycle when financial markets react to an updated set of information about changing economic conditions. The related adjustment of risk premia could open a feedback channel in response to already existing economic dynamics. Gilchrist et al. (2014) establish a general equilibrium model and use micro and macro-level data to analyze the effect of innovations in credit spreads on investments. According to their model incorporating financial frictions, an increase in uncertainty leads to a sharp and persistent widening of credit spreads that cause corporations to cut investment spending and decrease their leverage. The authors highlight the significance of financial risk premia as a primary source for a decline in investments and cast doubts on the relative importance of the ‘wait-and-see’ effect. Given their high frequency and availability, volatility indices of equity markets have been a preferred measure of uncertainty (Bekaert et al. (2013)) and served for benchmarking purposes of alternative uncertainty measures (Leduc and Liu (2016)). Caggiano et al. (2017) use the CBOE S&P 100 Volatility Index (VXO)<sup>34</sup> within a non-linear VAR model to analyze whether uncertainty is state-contingent based on U.S. data. Their results point to a larger effect of uncertainty during recessions with a sharp drop and subsequent recovery of unemployment and output. In expansionary phases, real economic variables react to a much lesser degree to an uncertainty shock with only limited evidence for overshooting.

---

<sup>33</sup> The idea can be attributed to work by Oi (1961), Hartman (1972) and Abel (1983).

<sup>34</sup> The authors acknowledge that the VXO capture a mixture between risk and uncertainty.

### ***3.1.4 Shape of Uncertainty***

As researchers tend to define uncertainty in their specific own ways without converging to a broadly shared concept, we first categorize the various approaches along the different moments of the distribution: the point estimate of the confidence level, the standard deviation, the skewness and the kurtosis. The most direct way of gaining an estimate about the level of uncertainty within the economy is to address uncertainty via surveys which represents the most observable component of uncertainty. Emerging new technologies for the screening of large datasets have provided researchers with new perspectives on point estimates of uncertainty in addition to the more traditional surveys. Baker et al. (2016) published a policy uncertainty index based on the screening of 12,000 newspaper articles for a specified word combination. This concept relies on the idea that journalists represent a qualitative filter that adequately reflects the level of uncertainty of economic decision makers. The obvious limitations to this approach is the ex-post selection of keywords and the reliance on the media to capture uncertainty in their writings.

A second group of literature considers in one form or another a measure related to the second moment of the distribution of uncertainty. A larger standard deviation is commonly interpreted as increasing uncertainty. Haddow et al. (2013) include amongst other variables implied volatility levels and dispersion among forecasters (GDP, company earnings) as input factors into their uncertainty index for the UK. Adrian and Brunnermeier (2016) propose a modified version of a VaR to detect systemic stress. The authors establish a VaR conditional on a financial institution being under distress relative to its median state and identify leverage, size, and asset price booms as predictors for periods of systemic risk. Representing another perspective through the lens of the standard deviation, Rossi and Sekhposyan (2015) consider forecast error distributions to describe the degree of uncertainty.

The literature that explicitly considers the third and the fourth moment, the skewness and the kurtosis, is most prominent in financial market literature given sufficient availability of price data, whereas fewer studies look at economic variables as well. Ferreira (2018) measures the skewness of cross-sectional stock market returns for financial firms in the US and finds superior predictive power as compared to other aggregate measures of uncertainty (Jurado et al. (2015)) or corporate bond spreads (e.g. Gilchrist and Zakrajsek (2012)). Based on data from 1926 to 2015, Ferreira (2018) highlights that financial firms diversify away non-systemic risks through asset portfolio choices and their returns provide a useful signal that bridges the gap between financial market valuation and real economic dynamics. Guvenen et al. (2015) analyze individual labor earnings for the US and find strong deviation from

lognormality in the presence of earnings shocks. In particular, results show significant negative skewness and high kurtosis in times of economic distress. Moreover, asymmetries between income cohorts and stages of the life-cycle arise as negative earnings shocks show higher negative skewness for older people given lower upside surprises and higher disaster risk.

### 3.2 Set-Up and Data of Economic Uncertainty

The conceptual framework of this study is deconstructing uncertainty along two dimensions: different moments of uncertainty and different economic agents.

#### 3.2.1 Moments of Uncertainty

One of the challenges that researchers are facing in their attempt to capture uncertainty is to clearly differentiate between the different moments. In particular, the overlap between the general confidence level and less observable components of uncertainty is a source of ambiguity. Hence, we employ four different moments: The first moment is the point estimate related to the general confidence level which is directly observable in surveys for producers and consumers and via implied volatilities for financial market participants; the second moment represents the standard deviation around this point estimate; the third moment measures the skewness; and the fourth moment captures the kurtosis. To quantify these measures, the analysis considers confidence surveys for the consumer and the corporate sector which include data for various subsectors.<sup>35</sup> This procedure allows for calculating the latter moments of the distribution based on the same dataset to achieve consistency with the first moment.

The first moment is defined as the average confidence level of the different subsectors of a survey. To facilitate the interpretation, we standardize and invert the time series. Hence, an increase of the index points to higher uncertainty.

The second moment, the standard deviation, is included to describe the overall dispersion of expectations according to the standard formula for the total population:

$$SD = \sqrt{\frac{1}{N} \sum_{i=1}^N [A_i - \mu]^2} \quad [3]$$

---

<sup>35</sup> The procedure for financial markets deviates slightly given different type of data.

N describes the number of observations; A denotes the respective value of the subsector (specific industry) of the survey; and  $\mu$  describes the mean which coincides with the first moment.<sup>36</sup> We assume that a wider distribution of confidence levels is indicative of a more uncertain prognosis. As economic agents do not form expectations in isolation, a higher dispersion of forecasts within a group of economic agents will likely lower their confidence in their own point estimates.

The third moment of the distribution, the skewness, describes the symmetry of the distribution:

$$SK = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^3}{\left( \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2} \right)^3} \quad [4]$$

If the shape of the distribution displays a longer tail to the right, skewness is considered to be positive. If a distribution is described by a longer tail to the left, skewness is negative. We examine whether outliers, that gather systematically on one of the ends of the distribution, carry informational value vis-à-vis the business cycle. Our hypothesis is that during periods of confidence, corporates and consumers gather around the average point estimate with negative outliers to the left, creating a negative skew. Following Keynes' animal spirits, we assume the behavior of economic agents to be pro-cyclical. Hence, a benign economic outlook will cause survey respondents to herd around higher levels in confidence indices with less room for positive outliers and more room for pessimists who, speaking in statistical terms, pull the mean below the median. In times of higher uncertainty, however, point estimates will shift to the left and eliminate the left skew with outliers emerging on the right. Bernhardt et al. (2006) develop a robust frequency test for herding behavior based on quarterly individual forecasts of professional analysts on earnings-per-share (EPS) announcements for the period between 1989 and 2001. The authors find that analysts systematically overshoot actual EPS in nearly 60% of the cases. This lends support to our hypothesis that in good economic times, a majority of forecasts is gathering around overly optimistic levels creating room for outliers to the downside with corresponding negative skewness.

---

<sup>36</sup> This nomenclature applies for the other formulas as well.

The fourth moment, kurtosis, is a measure to characterize the flatness of the distribution.

$$K = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^4}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2\right)^2} \quad [5]$$

The standard normal distribution is described by a value of 3. If a distribution is rather equally distributed around the point estimate, platykurtic, it displays thinner tails (values below 3). A peaked distribution is called leptokurtic, with higher consensus around the central estimate and fatter tails (values above 3). We assume that a leptokurtic distribution represents situations of high consensus among the majority of economic agents with more extreme outliers on both ends. Thus, we suspect binary events with diverging views on the extremes and herding behavior in the center to produce a leptokurtic shape. As kurtosis represents a latter moment, we are cautious to not interpret it on an isolated basis but rather in an integrated perspective together with the point estimate, the standard deviation and the skewness.

### **3.2.2 Economic Agents**

We determine the point estimate, the standard deviation, the skewness and the kurtosis for following economic groups: consumers, corporates and financial market participants. The dataset for the euro area spans from the introduction of the euro in January 1999 until June 2018 and applies a quarterly perspective.

Data on the consumer group is based on the European Commission Business and Consumer Survey<sup>37</sup> that considers currently more than 41,000 consumers across the European Union<sup>38</sup>. For this study, we identify 6 strictly forward looking survey questions<sup>39</sup> that assess expectations among consumers over the next 12 months on following perspectives: their financial situation, the general economic situation, unemployment expectations, future savings, major purchases and price trends. Each of these variables is provided for four different income cohorts which provides a total of 24 time series which we standardize. We then determine the four moments of uncertainty across the different time series for each point

---

<sup>37</sup> We assume that uncertainty in the broader European Union and the euro area is largely congruent as the largest contributors to GDP (except for the UK) are members of both communities.

<sup>38</sup> To achieve comparability, national statistics institutes use a harmonized questionnaire and a common timetable.

<sup>39</sup> We exclude variables that ask about the current state and past observations.

in time. The afore-mentioned variables are almost entirely positively correlated<sup>40</sup> after changing the sign of the outlook on unemployment. Hence, dispersion does not arise due to a change in direction of the point estimate. As the main hypothesis, we assume that greater variation within the dataset at a particular point in time across different questions and income cohorts is a sign for increasing uncertainty among consumers. While this assumption may be vulnerable to fundamental factors that drive a wedge between different types of expectations, we claim that the representative consumer cannot rationally adjust his outlook consistently across all items causing differences on the relative stance of each time series [Table 2].

On the corporate sector, we again consider survey data by the European Commission Business and Consumer Survey that is surveying 130,000 firms to infer the confidence levels of various industries.<sup>41</sup> For our analysis, we identify subsectors whose time series reaches back to the start of the EMU and exclude overlapping categories. The calculation of the different moments is then conducted across 34 standardized time series at a particular point in time. Given integrated supply chains, companies do not conduct their forecasting processes in isolation. Hence, we interpret a greater divergence between the confidence of sectors as a signal of uncertainty that could impact real economic decisions [Table 3].

Regarding financial market participants, the chapter applies a slightly different approach given the specific nature of available financial data [Table 4]. For the first moment, we refer deliberately to a parsimonious representation through the option-adjusted spread (OAS) on EUR denominated corporate bonds. According to existing literature, the OAS has the ability to capture investors' confidence in the current business cycle. Gilchrist et al. (2014) emphasize that changes in corporate bond spreads are the primary driver of the business cycle through the refinancing channel. The inclusion of corporate bond spreads as the first moment should provide insights into the discussion of how much of uncertainty can be attributed to the general confidence on credit markets and what is caused by the less observable parts of uncertainty expressed as the latter moments.

---

<sup>40</sup> 95.1% of covariances of the 24 time series are positive.

<sup>41</sup> The survey differs between countries and covers expectations on production, exports, hiring activity and the broader business sentiment.

**Table 2: Data on the Consumer**

<b>Consumer</b>
EA19: Fin Situation Next 12 Mo: Income 1st Quartile, Balance (SA, %)
EA19: Gen Eco Situation Next 12 Mo: Income 1st Quartile, Balance (SA, %)
EA19: Unemp Exp Next 12 Mo: Income 1st Quartile, Balance (SA, %)
EA19: Savings Next 12 Mo: Income 1st Quartile, Balance (SA, %)
EA19: Major Purchases Next 12 Mo: Income 1st Quartile, Balance (SA, %)
EA19: Price Trends Next 12 Mo: Income 1st Quartile, Balance (SA, %)
EA19: Fin Situation Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Gen Eco Situation Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Unemp Exp Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Savings Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Major Purchases Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Price Trends Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Fin Situation Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Gen Eco Situation Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Unemp Exp Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Savings Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Major Purchases Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Price Trends Next 12 Mo: Income 2nd Quartile, Balance (SA, %)
EA19: Fin Situation Next 12 Mo: Income 4th Quartile, Balance (SA, %)
EA19: Gen Eco Situation Next 12 Mo: Income 4th Quartile, Balance (SA, %)
EA19: Unemp Exp Next 12 Mo: Income 4th Quartile, Balance (SA, %)
EA19: Savings Next 12 Mo: Income 4th Quartile, Balance (SA, %)
EA19: Major Purchases Next 12 Mo: Income 4th Quartile, Balance (SA, %)
EA19: Price Trends Next 12 Mo: Income 4th Quartile, Balance (SA, %)
<b>1st Moment of Uncertainty: Average</b>
<b>2nd Moment of Uncertainty: Standard Deviation</b>
<b>3rd Moment of Uncertainty: Skewness</b>
<b>4th Moment of Uncertainty: Kurtosis</b>

**Table 3: Data on the Corporate Sector**

<b>Corporates</b>
EA19: Consumer Goods: Confidence Indicator, Balance (SA, %)
EA19: Investment Goods: Confidence Indicator, Balance (SA, %)
EA19: Intermed Goods, ex Mining/Quarrying: Confidence Indicator, Balance (SA, %)
EA19: Food And Bev: Confidence Indicator, Balance (SA, %)
EA19: Textiles: Confidence Indicator (SA, % Bal)
EA19: Wearing Apparel: Confidence Indicator (SA, % Bal)
EA19: Leather & Related Products: Confidence Indicator (SA, % Bal)
EA19: Wood Products: Confidence Indicator (SA, % Bal)
EA19: Paper Products: Confidence Indicator (SA, % Bal)
EA19: Reproduction of Media: Confidence Indicator (SA, % Bal)
EA19: Chemicals: Confidence Indicator (SA, % Bal)
EA19: Rubber & Plastic Products: Confidence Indicator (SA, % Bal)
EA19: Non-Metallic Mineral Products: Confidence Indicator (SA, % Bal)
EA19: Basic Metals: Confidence Indicator (SA, % Bal)
EA19: Fabricated Metal Products: Confidence Indicator (SA, % Bal)
EA19: Electronic & Optical Products: Confidence Indicator (SA, % Bal)
EA19: Electrical Equipment: Confidence Indicator (SA, % Bal)
EA19: Machinery & Equipment: Confidence Indicator (SA, % Bal)
EA19: Motor Vehicles & Trailers: Confidence Indicator (SA, % Bal)
EA19: Furniture: Confidence Indicator (SA, % Bal)
EA19: Other Manufacturing: Confidence Indicator (SA, % Bal)
EA19: Trade & Repair of Motor Vehicles: Confidence Indicator (SA, % Bal)
EA19: Sale of Motor Vehicles: Confidence Indicator (SA, % Bal)
EA19: Motor Vehicles & Accessories: Confidence Indicator (SA, % Bal)
EA19: Retail Trade, Excl Motor Vehicles: Confidence Indicator (SA, % Bal)
EA19: Retail Sale of Food/Beverages/Tobacco: Confidence Indicator (SA, % Bal)
EA19: Retail Sale of Other Goods: Confidence Indicator (SA, % Bal)
<b>1st Moment of Uncertainty: Average</b> <b>2nd Moment of Uncertainty: Standard Deviation</b> <b>3rd Moment of Uncertainty: Skewness</b> <b>4th Moment of Uncertainty: Kurtosis</b>

**Table 4: Data on Financial Markets**

<b>Financial Markets</b>	<b>Data since</b>
V2X Index (VIX)	Q1 1999
V1X Index (DAX Volatility)	Q1 1999
VCAC Index (CAC Volatility)	Q1 2000
10yr Rates Volatility	Q1 1999
XAUUSDV3M Curncy (Store of Value - Gold)	Q2 2002
EURUSDV3M Curncy	Q1 1999
EURJPYV3M Curncy	Q1 1999
EURAUDV3M Curncy	Q1 2000
EURCADV3M Curncy	Q1 2005
EURGBP3M Curncy	Q1 1999
IVOLCRUD Index (Energy)	Q4 2005
IVOLNATG Index (Energy)	Q4 2005
IVOLCCOP Index (Industrial)	Q4 2005
XAGUSDV3M Curncy (Industrial)	Q2 2002
IVOLCORN Index (Agriculture)	Q4 2005
<b>1st Moment of Uncertainty: Corporate OAS based on Barcalys EUR AGG Corporate</b> <b>2nd Moment of Uncertainty: Standard Deviation</b> <b>3rd Moment of Uncertainty: Skewness</b> <b>4th Moment of Uncertainty: Kurtosis</b>	

Source: Bloomberg

For the standard deviation, skewness and kurtosis, the study uses option implied volatilities of three segments: different asset classes (equity, rates and gold as a store of value), FX market (currency pairs versus the EUR to reflect flight-to-safety dynamics and fundamental trade flows) and commodities (energy, industrial and agriculture). To ensure data consistency among the various dimensions, we refer wherever possible to the 3m option implied volatility and convert daily values into quarterly observations via their average over the quarter. For the calculation of the second moment, we take the weighted average of the implied option values across the time series as soon as they become available given different starting dates. The third and fourth moment looks at the skewness<sup>42</sup> and kurtosis of the standardized implied volatilities across the different asset classes.

In a next step, we construct aggregate measures of uncertainty across the different economic agents. For the aggregate first moment and second moment, we use principal component analysis to combine the different point estimates<sup>43</sup> (factor loadings: Consumer 32%, Corporates 35%, Financial Markets 33%) and the standard deviation (factor loadings: Consumer 15%, Corporates 39%, Financial Markets 46%). The study refers to principal

<sup>42</sup> We assume that positive skewness indicates increasing concerns about an upcoming spike in volatility.

<sup>43</sup> The OAS for corporate bonds is not available before Q3 2000, hence, we combine data on the corporate sector and the consumer via a simple average until that point.

component analysis to describe the systemic nature of uncertainty expressed through the factor loadings of the first principal vector that explains most of the variation in the data. Hence, the first moment emerges almost equally from the three different economic groups, while the dispersion around the point estimate applies a higher weight to the dispersion within the corporate sector and financial markets. For the aggregate measures of the skewness and kurtosis, the study uses equal weighting given a later starting date of the financial time series and the decision to not standardize skewness and kurtosis given the more useful interpretation of their original scaling. This model set-up yields four aggregate indices representing the different moments of uncertainty. Each aggregate moment is made up of three sub-indices covering the different economic agents.

### 3.2.3 Construction of the VAR and the Impulse Response Functions

To estimate the impact of uncertainty on real GDP, we construct a VAR that includes two additional real economic variables reflecting broader business cycle dynamics and the four moments of uncertainty:

$$\begin{bmatrix} \text{GDP}_t \\ \text{IP}_t \\ \pi_t \\ 1^{\text{st}}\text{U} \\ 2^{\text{nd}}\text{U} \\ 3^{\text{rd}}\text{U} \\ 4^{\text{th}}\text{U} \end{bmatrix} = A + \text{Lag} \begin{bmatrix} \text{GDP}_t \\ \text{IP}_t \\ \pi_t \\ 1^{\text{st}}\text{U} \\ 2^{\text{nd}}\text{U} \\ 3^{\text{rd}}\text{U} \\ 4^{\text{th}}\text{U} \end{bmatrix} + \varepsilon_t \quad [6]$$

The four moments of uncertainty, 1<sup>st</sup>U, 2<sup>nd</sup>U, 3<sup>rd</sup>U, 4<sup>th</sup>U, reflect the aggregate vectors across the three different economic groups with t representing the respective quarter. For all real economic variables, the study considers the quarterly difference of the natural logarithm. For GDP, we include a measure of real GDP. For IP, we consider the Industrial Production Index excluding construction. For  $\pi$ , the analysis refers to a measure of core inflation represented by the HICP excluding energy and unprocessed food. We further test for four lags of the VAR representation. To infer the predictive value of each moment of uncertainty on real GDP via impulse response functions, we apply a one-standard deviation shock to the innovations of each uncertainty vector. We use the Cholesky decomposition of the covariance matrix and order the variables based on our hypothesis of the degree of endogeneity.<sup>44</sup>

---

<sup>44</sup> We assume that the real economic variables have a higher degree of endogeneity.

### 3.2.4 Out-of-Sample Assessment of Forecast Accuracy

In order to assess whether the different moments of uncertainty contribute to the forecasting quality of the model, we estimate rolling out-of-sample GDP forecasts for the one quarter horizon. We proceed by estimating the VAR from Q1 1999 until Q1 2008 which is the last quarter before growth of real GDP hits negative territory. We start by forecasting GDP for the next quarter and calculate the following error term:

$$\text{Root Sum Squared Error} = \sqrt{\frac{\sum_{i=1}^N (\text{Forecast of } GDP - GDP)_i^2}{N-1}} \quad [7]$$

We repeat the same exercise moving one quarter forward while keeping the starting date of the VAR fixed at Q1 1999 until we reach Q1 2018. The variable  $n$  represents the number of forecasts which is 41 for this set-up. We estimate this forecast error for 5 different models. The benchmark model 1 represents a parsimonious definition containing only the three real economic variables. Models 2 to 5 include an increasing number of uncertainty vectors beginning with the first moment and adding stepwise the standard deviation, the skewness and the kurtosis.

### 3.2.5 Validation of Results

A common argument in literature is the dominant effect of the point estimate of confidence on the latter moments of uncertainty. If we observe that any of the latter moments (standard deviation, skewness and kurtosis) increases the model's forecasting accuracy, we will examine whether this effect is primarily driven by the first moment or by a genuine exogenous shock coming from the particular moment itself. Following a purging procedure described in Hatzius et al. (2010), we estimate a linear OLS regression model with the respective latter moment as the determinant variable and the first moment as the explanatory variable. We interpret the standardized error terms as the latter moment purged of the first moment and re-estimate the out-of-sample forecasting model.

## 3.3 The Effects of Economic Uncertainty

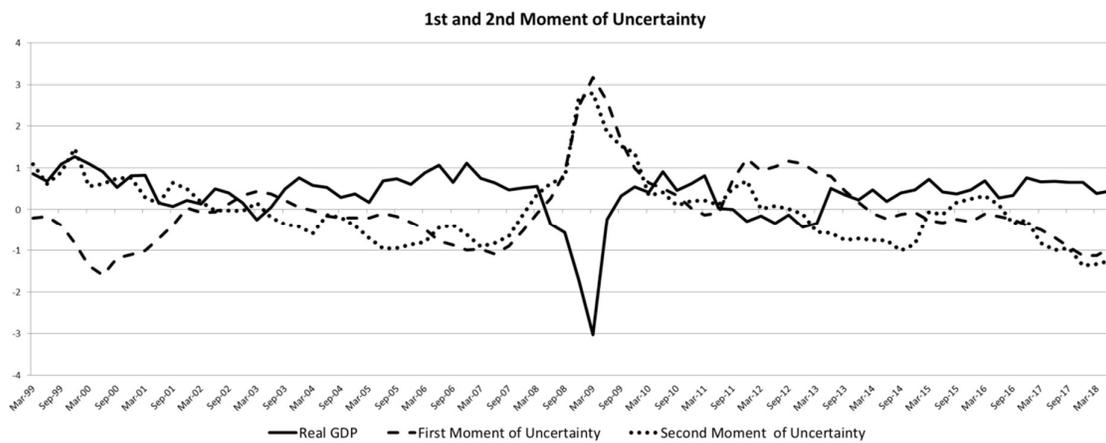
In a first step, we describe the nature of the different moments of uncertainty qualitatively vis-à-vis the business cycle. Secondly, we shock the different uncertainty variables by one standard deviation of their innovations and examine the effect on GDP. Third, we assess whether adding different moments of uncertainty increases the forecast accuracy of a VAR

model via rolling out-of-sample forecasts and validate subsequently the results with regard to potential endogeneity.

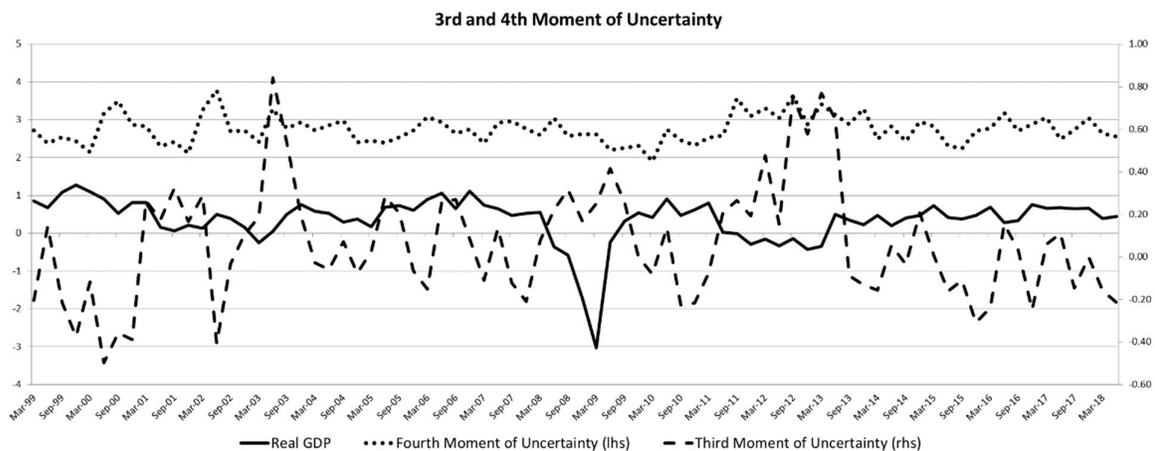
### 3.3.1 Behavior of the Different Moments

All four moments are negatively correlated with GDP ranging from -0.77 to -0.05 in decreasing order. In line with our initial assumption, an increase of each moment is associated with a decrease in GDP growth for the first three moments and less conclusive results for the fourth moment (see Table 5 and Figure 5 and 6 for this).

**Figure 5: 1<sup>st</sup> and 2<sup>nd</sup> Moment of Uncertainty**



**Figure 6: 3<sup>rd</sup> and 4<sup>th</sup> Moment of Uncertainty**

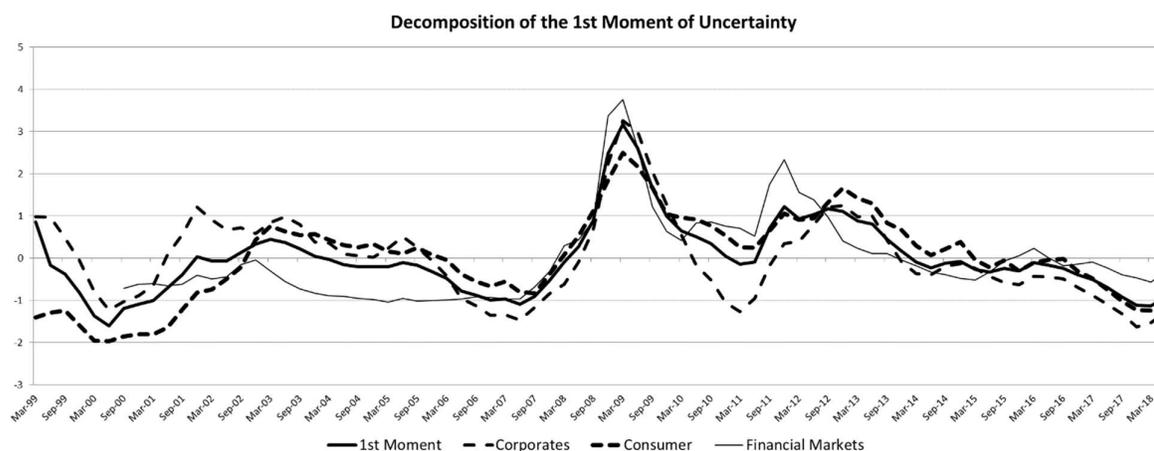


**Table 5: Correlation of the Variables**

	Real GDP	IP	Core Inflation	1st Moment	2nd Moment	3rd Moment	4th Moment
Real GDP	1.00	0.89	-0.07	-0.77	-0.59	-0.38	-0.05
IP	0.89	1.00	-0.09	-0.59	-0.51	-0.31	0.03
Core Inflation	-0.07	-0.09	1.00	-0.05	0.06	0.16	0.07
1st Moment	-0.77	-0.59	-0.05	1.00	0.62	0.50	-0.02
2nd Moment	-0.59	-0.51	0.06	0.62	1.00	0.10	-0.14
3rd Moment	-0.38	-0.31	0.16	0.50	0.10	1.00	0.18
4th Moment	-0.05	0.03	0.07	-0.02	-0.14	0.18	1.00

The first moment of uncertainty [Figure 7] peaks three times during the last 20 years and tracks closely the GDP dynamics with a correlation of -0.77. Not only does the first moment reflect all three periods, in which economic growth turned negative (the economic contraction in Q1 2003, the GFC, the European peripheral debt crisis), but it also captures the magnitude of each of these economic periods very well. The index reaches its highest level during the GFC by increasing to 3.2 standard deviations above historical levels. From its through in Q2 2007, the index needs 7 quarters to hit its global peak in Q1 2009. This period coincides with the steepest quarterly decline of GDP during the GFC of -3%. During the European peripheral debt crisis, the amplitude of the index is more contained at 1 standard deviation above historical levels, representing the second largest peak. However, the first moment maintains an average level of 1 standard deviation for approx. 7 quarters which reflects strained confidence levels until the preliminary resolve through concerted action taken by the ECB and the European Commission. The third largest peak of the index occurs in Q1 2003, when growth of the euro area was lingering in negative territory for about a quarter. In line with the mild level of economic distress at that time, the uncertainty index enters positive territory but peaks already at 0.4 standard deviations. For the rest of the period, the index remains below zero without major fluctuations which underlines the benign economic periods between Q4 2003 to Q4 2007 and Q2 2013 to Q2 2018. The qualitative assessment of the first moment lends support to the hypothesis that the underlying input factors are largely representative of business cycle dynamics.

**Figure 7: Decomposition of the 1<sup>st</sup> Moment of Uncertainty**

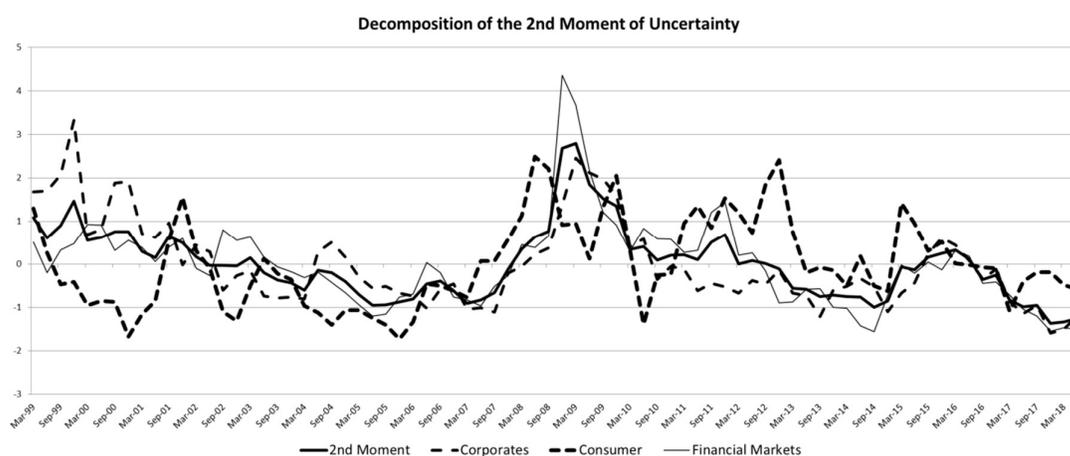


The second moment of uncertainty [Figure 8] is also strongly negatively correlated with GDP growth at  $-0.59$ . Given that the calculation of the first and the second moment was conducted based on the same dataset (with the exception of financial data), we interpret the second moment as the level of conviction that consumers, corporates and financial markets have about their first moment confidence estimate. Considering positive correlation of  $0.62$  between the first and the second moment, the observer is inclined to associate periods of high uncertainty with higher dispersion around the point estimate. On the same note, periods of lower uncertainty are associated with higher unanimity in the outlook. However, as we deconstruct this summary statistic into sub-periods, we learn that the overall positive correlation between the first and the second moment of uncertainty can be split into a pre-crisis period before the GFC exhibiting actually negative correlation and a period with very strong co-movement thereafter. For the period between Q1 1999 and Q4 2007, results indicate a correlation of  $-0.17$  which highlights that the second moment did not behave pro-cyclically. During the first years after the formation of the euro area, the point estimate of uncertainty (first moment) shows generally high confidence among economic agents. The second moment, however, reveals a sustained higher dispersion around the point estimate within the corporate sector, among consumers and on financial markets representing uncertainty lingering below the surface. In fact, the high level of dispersion around this estimate is only surpassed by the levels observed during the GFC.

Looking at the period from Q1 2008 to Q2 2018, the correlation of both moments changes substantially and stands at  $0.83$ . The strong increase of uncertainty during the GFC coincides with less consensus among economic agents about their confidence estimate. We

observe similar co-movement of both moments for the time period between Q2 2015 and Q2 2018 with a correlation of even 0.90. Despite potentially disruptive events (e.g. Brexit, U.S. election in 2016, the Greek debt crisis), both indices remain consistently low which underlines a high degree of unanimity among economic agents. In order to validate our initial belief of a structural break in the relationship between both time series, we conduct a test for structural change (Chow, 1960) that assumes that the first moment is explanatory for the second moment.<sup>45</sup> The model supports our initial assumption of a structural break in Q1 2008 (last quarter before negative GDP growth) and rejects the null hypothesis of coefficient stability at the 1% significance level.

**Figure 8: Decomposition of the 2<sup>nd</sup> Moment of Uncertainty**

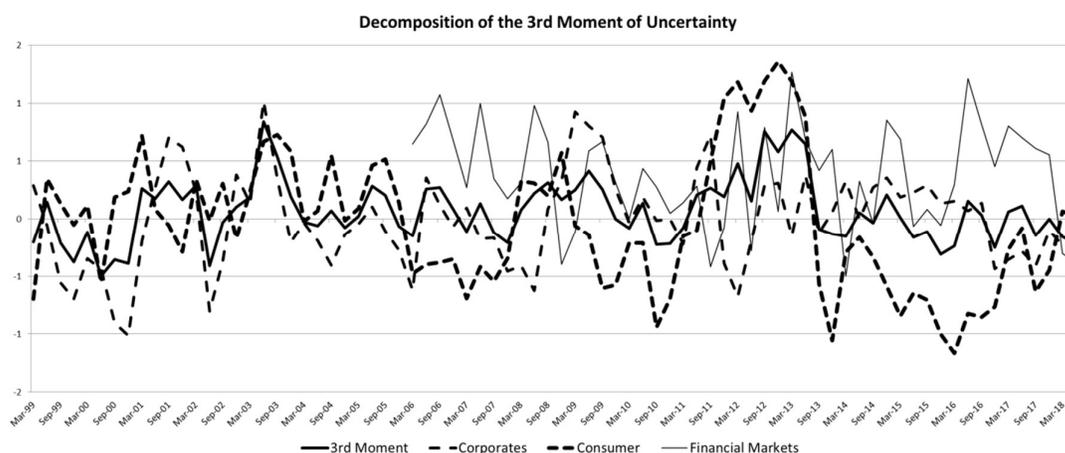


The third moment [Figure 9] is negatively correlated with GDP at -0.38 and positively correlated with the first and second moment of uncertainty. Providing insights into the symmetry of the distribution, positive skewness is associated with negative growth. During periods of benign economic conditions, we tend to observe a moderately left skew with only a few outliers on the left-hand side of the distribution. As most market participants gather on the positive spectrum, this creates ample room on the left-hand side of the confidence distribution for outliers who create the corresponding skew. When the crisis hits, people tend to revise their confidence level downward and collective herd behavior forces the median to fall below the mean of the distribution. At later stages of a crisis, the sustained positive skew is likely to be driven by positive outliers on the right-hand side who expect improving

<sup>45</sup> As literature often assumes that the first moment has an effect on the second moment of the distribution, we model the Chow test with the first moment as the explanatory variable.

economic prospects.<sup>46</sup> Over the last two decades, we can observe positive skewness peaking three times. These local maxima coincide again with the three economic downturns that also come with a spike in the first moment. However, the nature and amplitude of these increases differ with the European peripheral debt crisis representing the most persistent positive skewness. During the period between Q1 2011 and Q1 2013, the positive skewness continuously rises while the first moment remains steadily at the same uncertainty level. A similar gradual increase of the positive skew is evident during the GFC, however, to a significantly lower amplitude.

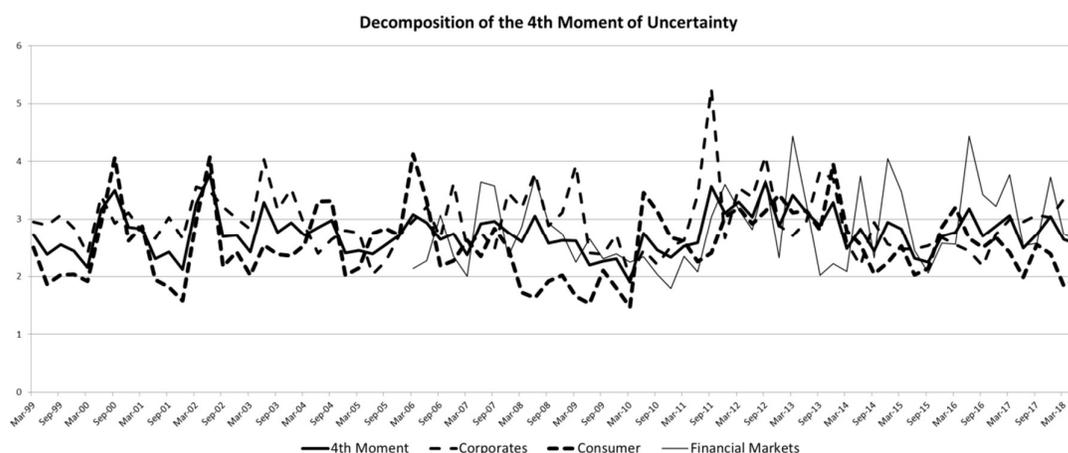
**Figure 9: Decomposition of the 3<sup>rd</sup> Moment of Uncertainty**



The fourth moment of uncertainty has a correlation of -0.05 with GDP growth and a correlation between -0.14 and 0.18 with the three other moments of uncertainty [Figure 10]. Hence, it appears to be almost uncorrelated with the business cycle. Over the last two decades, there is only the period between Q3 2011 and Q2 2013 in which the fourth moment attributes a persistent leptokurtic shape to uncertainty. This suggests that most of the economic agents have gathered around the points estimate with a few extreme outliers. The latter characteristic could be explained by the very binary nature of the redenomination risks that were surfacing during the European peripheral debt crisis. In contrast, the period leading up towards the GFC and the economic downturn itself did not coincide with a higher dispersion of confidence estimates in the tails of the distribution.

<sup>46</sup> For the financial time series, periods of crisis show also a positive skew with extreme outliers on the upper volatility spectrum.

**Figure 10: Decomposition of the 4<sup>th</sup> Moment of Uncertainty**

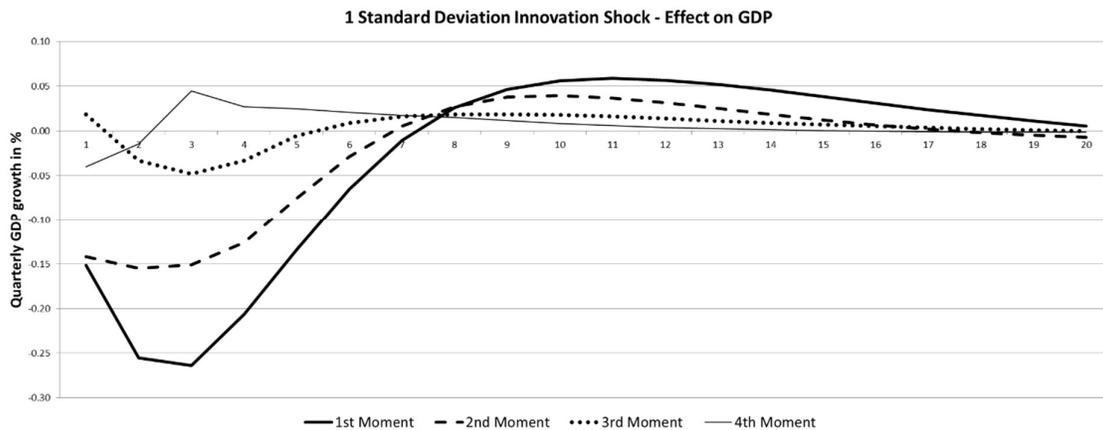


### 3.3.2 The Effect of Uncertainty on GDP

The impulse response function is based on a VAR with a lag structure of 2 based on the AIC criterion. This result suggests that uncertainty and real economic variables impact one another with a lag of up to 6 months. To further examine the role of the various economic groups, we differentiate in a second step between consumers, corporates and financial markets.

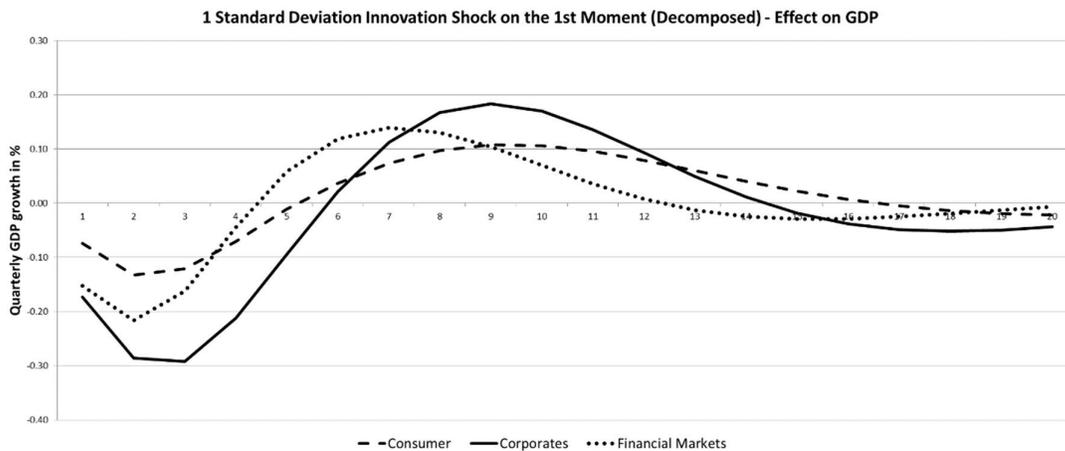
A one standard deviation shock to the first moment of uncertainty [Figure 11] leads to a cumulative decline in GDP of 1.1% over the first two years. While the effect during the first year is -0.9%, the impulse on GDP leaves negative territory by the 8<sup>th</sup> quarter and leads to some degree of growth overshooting in the annual range of 0.2 % before it dies out after additional 3 years. As the overshooting makes up for around half of the detraction, the model suggests that an uncertainty shock has a persisting effect on the level of GDP but not on the growth rate. An innovation to the second moment leads to a decline of GDP by -0.6% over the first two years with a subsequent moderate increase of GDP. Results mirror the findings for the first moment, however, with a lower amplitude. Even though the impulse response function for a shock on the third moment of uncertainty shows overall similar dynamics in its impulse on GDP, the effect is significantly lower in absolute terms (-0.1% of GDP in the first year). With regard to the kurtosis, the impulse response on GDP to a shock to the fourth moment is negligible (0.02% in the first year).

**Figure 11: Impulse Response Function and Effect on GDP**



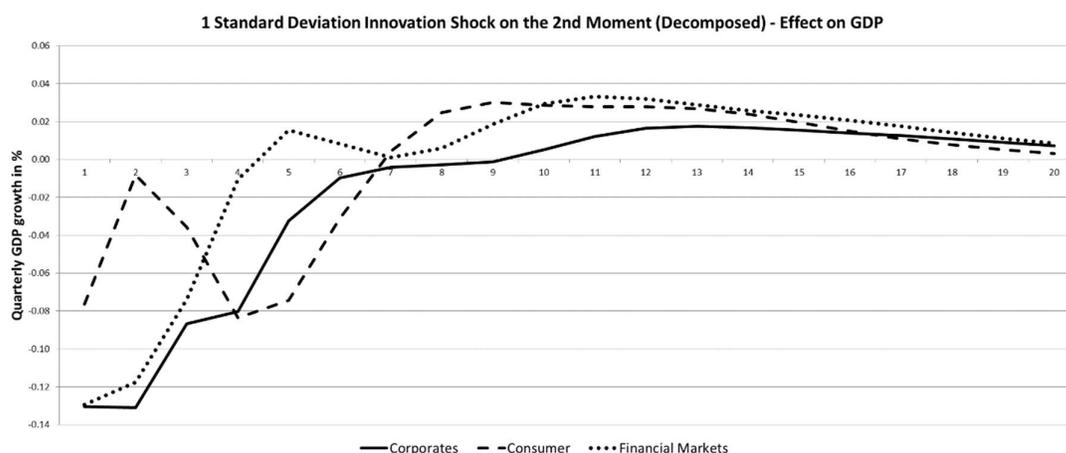
Decomposing the shock to the first moment of uncertainty into the vectors' three subcomponents through individual impulse response functions, we can attribute the largest impact to the corporate sector by -1% GDP growth in the first year [Figure 12]. Interestingly, financial markets exert a similarly sized shock in the first quarter, however, the effect is much less persistent and returns to a positive impulse on growth already after the first year.

**Figure 12: Decomposition of the Impulse Response Function (1<sup>st</sup> Moment)**



With regard to the decomposition of the second moment of uncertainty, results confirm that a financial markets shock is again less persistent in its effect on the real economy compared to an impulse stemming from the other two economic agents [Figure 13]. Despite the overall lower amplitude, the consistency across the different agents lends credibility to the idea that positive skewness carries significant informative value regarding a decline in GDP.

**Figure 13: Decomposition of the Impulse Response Function (2<sup>nd</sup> Moment)**



### 3.4 Predictive Value of Uncertainty in GDP Forecasts

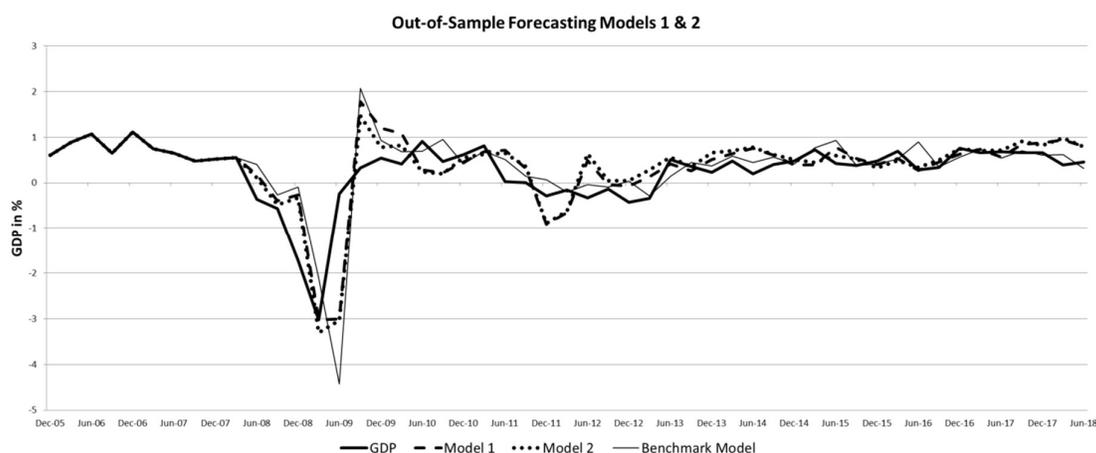
In this section, we examine how the addition of the four moments affects the VAR model’s forecast accuracy on real GDP growth over the one-period horizon and subsequently test for the role of endogeneity.

#### 3.4.1 Results of the Different Forecasting Models

We estimate four VAR models starting with the three real economic variables and the first moment of uncertainty. For each additional model, we add another moment of uncertainty until we reach the full specification as outlined in section 3.2.3. The initial calibration considers the period between Q1 1999 and Q1 2008, which represents the last quarter before growth turned into negative territory during the recession of 2008-2009. We re-estimate the model by adding one additional quarter until we reach Q1 2018 and assess the root sum squared error term. To evaluate the relative performance, the study considers first a parsimonious benchmark model based on the three real economic variables [Table 6 and Figure 14].

The benchmark model produces a root sum squared error of 0.81. The reason for this relatively large forecast error can be traced back to the GFC between Q1 2008 and Q3 2009, which yields on an isolated basis a root sum squared error of 2.02. As the calibration period between Q1 1999 and Q1 2008 does not include a major downturn, the model’s error term is rather large for the first economic contraction. For the second recession caused by the European peripheral debt crisis, the forecast accuracy of the model improves significantly yielding only a forecast error of 0.27 for this isolated period.

**Figure 14: GDP Forecast – Benchmark Model, Model 1 and Model 2**

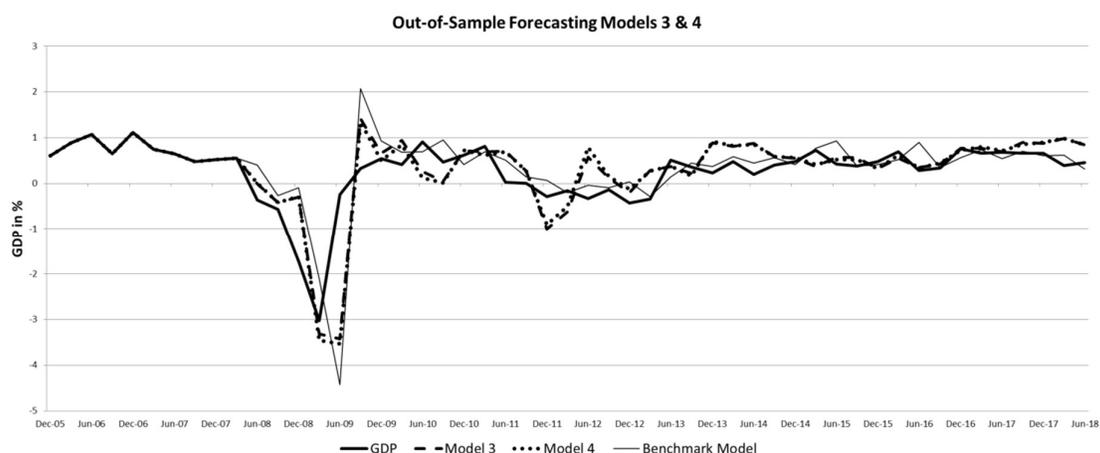


**Table 6: Results of the Forecasting Models**

	Model Components							Root Sum Squared Error		
	Real GDP	Industrial Production	Core Inflation	1st Moment of Uncertainty	2nd Moment of Uncertainty	3rd Moment of Uncertainty	4th Moment of Uncertainty	Full Period	Recession 2008-2009	Recession 2011-2013
Benchmark Model	X	X	X					0.81	2.03	0.27
Model 1	X	X	X	X				0.65	1.42	0.53
Model 2	X	X	X	X	X			0.63	1.38	0.60
Model 3	X	X	X	X	X	X		0.68	1.50	0.58
Model 4	X	X	X	X	X	X	X	0.70	1.54	0.62

The addition of the first moment of uncertainty (Model 1) improves the forecast accuracy over the total horizon substantially and generates a root sum squared error of 0.65. This is due to a better performance during the first recession with error statistics of 1.42. The GDP forecast of Model 1 predicts growth of -3.03% in Q1 2009 (actual growth -3.02%) versus a forecast of -2.11% based on the benchmark model. Hence, the first moment of uncertainty seems to adequately capture the amplitude of the recession during the GFC. However, Model 1 fails to capture the quick rebound of growth back to -0.24% in the subsequent quarter. Model 2, which incorporates both the first and second moment of uncertainty, improves the forecast accuracy further with an error term of 0.63. The addition of the third moment and the fourth moment of uncertainty, however, decreases the model quality with an error term of 0.68 for Model 3 and 0.70 for Model 4 [Figure 15].

**Figure 15: GDP Forecast – Benchmark Model, Model 3 and Model 4**

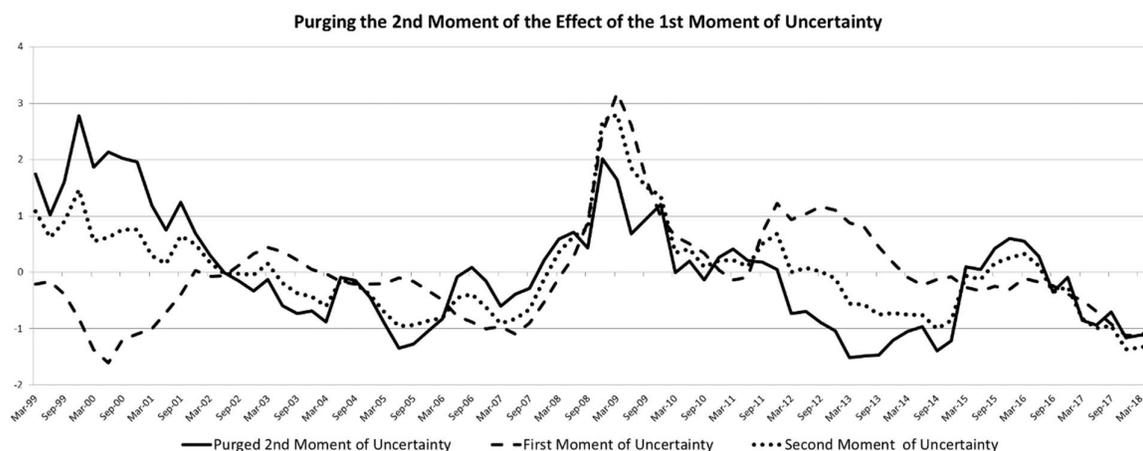


We conclude that augmenting the benchmark model with the first moment of uncertainty clearly yields a significant improvement. On the addition of the second moment, we remain cautious and further investigate the relationship between the first and the second moment of uncertainty in the next section.

### ***3.4.2 Purging for the Exogenous Component of the Second Moment***

Results of the previous section provide some evidence that the second moment increases the forecasting ability of the VAR model on GDP growth. However, the question arises to what degree the dynamics of the second moment are actually driven by the first moment of uncertainty. To purge the second moment from the effect of the point estimate of confidence, we apply a regression method used by Hatzius et al. (2010). We estimate a linear OLS regression model with the second moment as the determinant variable and the first moment as the explanatory variable. Results suggest that 31% of the second moment can be explained by variation of the first moment. For the perspective of this analysis, we interpret the standardized error terms as the exogenous component of the second moment [Figure 16].

**Figure 16: The Exogenous Component of the 2<sup>nd</sup> Moment of Uncertainty**



The purged index reveals that the highest degree of dispersion occurs in the early days of the newly formed euro area. The levels are comparable to the heightened dispersion during the GFC. According to this revised index of the second moment, the dispersion of uncertainty during the European peripheral debt crisis was even below historical averages and rises again into positive territory during the flare-up of recession fears between Q3 2015 and Q2 2016. To quantify the predictive value of the purged index, we re-estimate Model 2 by replacing the second moment by the purged index of the second moment. The root sum squared error of the rolling GDP forecast remains at 0.63 which is consistent with the results of the unpurged version. Hence, we conclude that the second moment carries additional informative value that is not captured in the first moment of uncertainty.

### 3.5 Concluding Remarks on Economic Uncertainty

We use the four moments to quantify uncertainty across consumers, producers and financial market participants. All four moments are negatively correlated with GDP growth with correlation coefficients ranging from -0.77 to -0.05 in increasing order. The qualitative assessment of the first moment lends support to the idea that point estimates of the confidence level are strongly representative of business cycle dynamics. The second moment of uncertainty is also strongly negatively correlated with GDP and displays how unanimous economic agents are about their point estimate. The analysis of the third moment reveals that positive skewness is associated with negative growth. While the initial increase of the skewness during a crisis is probably driven by herd behavior, the continuous increase during a crisis could reflect optimistic outliers who act as harbingers for the recovery. The assessment

of the fourth moment does not allow for firm conclusions about its relationship with the business cycle.

By quantifying the impact of uncertainty, impulse response functions suggest that a one standard deviation shock to the innovations of the first moment of uncertainty leads to an initial cumulative decline in the level of GDP of -1.1% over the first two years which is reduced by half due to an overshoot of GDP growth over the subsequent years. By decomposing the shock on the first moment of uncertainty into its three sectors, we can attribute the largest impact to the corporate sector and observe the effect of financial markets being equally strong in the beginning but fading much quicker. A shock to the second and third moment of uncertainty causes similar dynamics like the first moment but with lower amplitude, indicating a decreasing economic impact. The kurtosis is negligible with regard to the impact on GDP.

We conclude that augmenting a parsimonious forecasting model on GDP by the first and second moment of uncertainty clearly improves overall forecast accuracy. As we remove the effect of the first moment on the second moment through a purging procedure, we find evidence verify that the second moment carries informational value that is independent of the first moment improving the forecasting model further.

## 4. The Effect of the ECB's Forward Guidance on Interest Rate Forecasts<sup>47</sup>

Not only since the beginning of the prolonged low-interest rate environment have central banks been carefully shaping their communication policy to influence public expectations on the future path of monetary policy. Within the existing monetary policy framework, statements have been ranging from the assessment of future economic conditions, which implicitly convey future policies, to the explicit announcement of future monetary policy. Already in 1997, the Reserve Bank of New Zealand (RNBZ) has started to publish an interest rate forecast, which was soon adopted by the Norges Bank and the Sveriges Riskbank. In contrast to this purely qualitative communication strategy, the current connotation of forward guidance (FG) is of more quantitative and exogenous character.

The main driver for the emergence of the current form of FG has been the need to steer market expectations at the ZLB. First, the effectiveness of changing the short-term

---

<sup>47</sup> This chapter is based on: Fendel et al. (2019c): The effect of the ECB's forward guidance on interest rate forecasts, Unpublished WHU Working Paper Series.

policy rate has been impaired by downward rigidity. Hence, gaining control of the medium and longer part of the interest rate curve becomes more imminent. Second, deflationary concerns have been increasingly present with a higher need to anchor medium-term inflation expectations given less room at the ZLB. Third, market participants have faced higher uncertainty in predicting monetary policy as central banking at the ZLB for a long period of time is unprecedented in history.

In fact, statements of the likely interest rate path can be broadly categorized into three groups: (i) Prospects of economic conditions, (ii) reaching stated policy objectives, and (iii) a time component. The first category of FG makes the future path of monetary policy contingent on the future macroeconomic environment.<sup>48</sup> Hence, a central bank still maintains some degree of flexibility to change course in case economic realities are shifting without risking their credibility. At the same time, this communication policy provides markets with some degree of assurance. The second category of FG relates to reaching mandated policy goals such as the inflation rate, economic growth or unemployment rates.<sup>49</sup> This type of FG represents an extension of the first category, as it relates to the goal variables that are ultimately influenced by economic conditions. However, it is more explicit by making future monetary policy accountable in reaching stated policy goals. Even though it carries a higher degree of commitment, economic agents are aware of the limitations of a central bank in its ability to influence economic transmission channels. Hence, the possibility of changing monetary actions and corresponding uncertainty remains. The third category attaches a particular date to the duration of FG.<sup>50</sup> Under this communication strategy, a central bank deliberately limits its flexibility to react to changing circumstances for a certain period of time and deviating from this policy inhibits the risk of a loss in credibility. From a theoretical perspective, it should provide markets with the highest degree of confidence in future monetary policy. Against the background of the diverse nature of FG, this study applies a parsimonious definition of FG and refers to the official starting date as suggested by the ECB itself.

This study analyzes the impact of the ECB's FG on the forecast error of financial markets participants regarding the interest rate level and the slope of the yield curve for the period from Q1/2010 to Q4/2018. We refer to overnight index (OIS) swap rates as the relevant forecasts and purge the prediction error of several macroeconomic and financial

---

<sup>48</sup> The Bank of Japan has introduced this type of macro-conditional FG in 1999.

<sup>49</sup> The Bank of England has introduced goal-based FG in 2013 with explicit reference to unemployment numbers.

<sup>50</sup> The Federal Reserve has referred to such calendar-based FG in 2011.

variables to gain a pure representation of the exogenous forecast error. To quantify and isolate the effect of FG, we refer to the absolute deviation of forecasts from actual rates and further control for variables representing unconventional monetary policies.

The chapter is structured as follows: Section 4.1 categorizes the ECB's FG and proceeds with a literature review of the transmission channels of FG in section 4.2. Section 4.3 examines the effect of FG on interest rate predictability. Section 4.4 covers the methodology and data sources. Section 4.5 entails the results with subsequent robustness tests in section 4.6. Section 4.7 concludes.

#### **4.1 The ECB's Forward Guidance**

According to the ECB itself, July 4<sup>th</sup> 2013 marks the official introduction of FG to the European currency area (ECB, 2014). On that day, the ECB Governing Council in person of its president Mario Draghi assured financial markets that key interest rates are expected to “*remain at present or lower levels for an extended period of time*” (Draghi, 2013). This type of FG borrows elements of the third category by introducing a weak time commitment which, however, lacks the date-specific nature. The communication policy of the ECB also added a goal-specific component by referring to “*the overall subdued outlook for inflation extending into the medium term*” during the introductory statement of the press conference. Although the Governing Council has long before commented on anchoring inflation expectations, the ECB became more explicit during the phase of unconventional monetary policy in referencing to observable market rates such as the 5y5y break-even inflation rate<sup>51</sup> as a gauge for price stability. In addition, the ECB continued to provide their assessment of various economic parameters such as the “*high degree of unutilized capacity, and subdued money and credit creation*” (Draghi, 2014).

Hence, the type of FG adopted by the ECB has emerged as a combination of the three different categories: A mild date-based and goal-specific future monetary policy that is conditional on the anchoring of inflation expectations weighing the risks to the broader economy. While July 4<sup>th</sup>, 2013 represents the ECB's self-proclaimed start of FG, the debate of the actual (i.e., de facto) start of this new form of communication policy is not unambiguous. At the height of the European peripheral sovereign debt crisis in June 2012 when markets were testing the possibility of currency redenomination of southern European countries, Mario Draghi held an infamous speech in London reassuring the currency area that the ECB will “*do whatever it takes*” (Mario Draghi, 2012) to preserve the euro within the ECB's

---

<sup>51</sup> The 5y5y break-even inflation rate is the market-implied inflation rate over a five year time period in 5 years' time.

mandate. Although it was less specific in its future actions, it was not less significant in its importance. Hence, our later analysis will leave some room for a revised period of FG.

## **4.2 Transmission Channels of Forward Guidance**

The theoretical foundations of FG suggest three transmission channels. First, FG increases the control of central banks over medium to longer dated maturities on the yield curve. A central bank gains stronger influence on the parts of the yield curve that are further out on the maturity spectrum by committing to a certain policy path of future short-term policy rates. Both consumers and corporations will be affected through the refinancing channel exerting a direct influence on consumption, housing, and investments. For the previous years of unconventional monetary policy, this channel should manifest itself in a stronger flattening of the yield curve as compared to phases of expansionary monetary policy based on ‘traditional’ interest rate policy. A second channel implies increasing credibility of stated policy objectives which should help anchoring expectations. Particularly at the ZLB, the public testimony of sustained lower rates provides the central bank with an additional tool to address deflationary tendencies. A third channel is higher predictability of future interest rates which can lead to changes in the term premium. By reducing the probability of monetary policy surprises, FG could lower volatility of financial market interest rates and decrease uncertainty among corporations with respect to refinancing conditions. Hence, this transmission channel should lower the responsiveness of financial markets to monetary policy announcements and stabilize lending conditions for the real economy.

Becker and Smith (2015) provide a general assessment of the functioning of the transmission channels and find that a FG shock at the ZLB has a positive and significant positive effect on US employment and the price level. To compare this communication tool to conventional interest rate cuts, the authors estimate a VAR for the period between 1979 and 2008 and a similar model for the period thereafter when the Fed started to engage in FG at the ZLB. Results indicate that FG needs to be larger in size than a regular rate cut to achieve similar results (with a ratio of 5 to 1). This is in line with the well-known FG puzzle (Del Negro et al, 2012), which points to the discrepancy between the theoretical assertion of DSGE models that FG is highly effective and the more mixed empirical results.

In fact, one source of ambiguity stems from the nature of the announcement which Campbell et al. (2012) have classified into Odyssean or Delphic FG. The latter type of communication policy is of more implicit nature as it conveys expectations about future economic fundamentals and points to the likely policy response under a transparent and

functioning policy framework. Odyssean FG, to the contrary, represents a firmer commitment to future monetary policy measures in response to unexpected economic developments that cannot be effectively addressed by conventional monetary policy. Under this particular regime of FG, a central bank binds itself to promises of the past and increases its credibility at the cost of future flexibility. Andrade and Ferroni (2016) analyze the impact of ECB statements on inflation expectations and categorize the communication policy of the ECB over 15 years into a binary classification system (Odyssean vs. Delphic FG). The authors find that both types of communication policy co-existed, however, with different relative importance.<sup>52</sup> Since 2002, ECB policy has been dominated by the Delphic component, while Odyssean FG has become more relevant in later years. In our study, we focus on those later years of the euro area and the effects of FG on the third transmission channel – higher interest rate predictability and lower interest rate variability.

### **4.3 Interest Rate Predictability under Forward Guidance**

The empirical literature on the predictability of interest rates and the effect of central bank communication often starts with the weak form of interest rate FG where policymakers publish the expected path of interest rates. Goodhart and Lim (2011) assess the quality of interest rate forecasts based on market implied rates for the UK (Libor rates and the government yield curve) and forecasts made by the RNBZ. To test for the unbiasedness hypothesis of forecasts, their analysis uses the Mincer-Zarnowitz regression (Mincer and Zarnowitz 1969) that considers the difference of interest rate forecast and the realized yield over different horizons including a modification that focuses solely on the deviation by removing the absolute yield level. Results indicate high forecasting quality for the next quarter with rapidly decreasing forecasting quality after 6 months. Hence, the authors suggest a hybrid forecast combining an educated guess for the short-term and the assumption of unchanged rates for the medium term.

Kool and Thornton (2015) throw the spotlight on the RNBZ, the Norges Bank, the Sveriges Riskbank and the Federal Reserve System (Fed) and estimate the effect of the communication policy on interest rate predictability. While FG guidance of the former three central banks is largely restricted to interest rate forecasts over the three-year horizon, the study defines for the Fed two distinct periods of FG reflecting the change from time-contingent to state-contingent FG in December 2012. The authors define the prediction error

---

<sup>52</sup> For an analysis of different types of FG with respect to the Fed, see Fendel et al. (2017).

as a loss function<sup>53</sup> based on survey data of interest rate forecasts for the three and twelve-month horizon and examine the coefficient of a dummy variable reflecting FG. Results indicate a significant impact of FG for the RBNZ and limited support for FG efficiency for the other central banks. In a robustness check, the authors further include benchmark variables capturing the forecast error for countries whose central banks do not engage in FG and test against a random walk. Findings for New Zealand cannot be substantiated, however, there appears to be evidence that forecasters in the case of New Zealand converge.

Andersson and Hofmann (2009) use two types of benchmarks to compare the effectiveness of central banks publishing an expected interest rate path: First, they compare central banks with FG to those with similar characteristics but different communication policies (RBNZ and Riksbank). Secondly, the authors analyze different regimes of the same central bank, comparing the period before and after the introduction of publishing the interest rate forecast (Norges Bank). Controlling for domestic and foreign economic news, the authors regress daily changes in forward rates on a target surprise and a path surprise variable. Results suggest that interest rate predictability does not increase further if central banks have already operated under transparent and credible goal variables. However, results for the Reserve Bank of New Zealand indicate higher control over the mid-part of the interest rate curve which responds stronger to the publication of the interest rate path than its benchmark (announcements made by the Riksbank).

Hubert and Labondance (2018) analyze the impact of ECB's FG on different OIS rates ranging from one month to ten years forward. The authors conduct a high-frequency event study based on different regression models (OLS, TARCh and GARCH) and include FG as a dummy variable. Differentiating further between different instances of FG, the study identifies three events, including July 4<sup>th</sup> 2013, January 9<sup>th</sup> 2014 and the announcement of QE on January 22<sup>nd</sup> 2015. The authors highlight that no other monetary policy decisions were communicated between the first two dates. To control for other monetary policy decisions taken, the authors account for monetary policy shocks including the shadow interest rate by Krippner (2013, 2014), a high-frequency method by Kuttner (2001) as well as a vector covering daily price fluctuations of the oil price, the EuroSTOXX 50 and the Economic Sentiment Indicator (ESI). Results indicate that ECB's FG has a persistent effect across the whole term structure with an increasing impact further out on the curve with OIS rates falling by 5 basis points at the three and five-year horizon following an FG announcement.

---

<sup>53</sup> The loss function represents the absolute and squared deviation of the forecast from realized interest rates.

## 4.4 Data and Methodology

To quantify the impact of FG on interest rate predictability, the set-up of the study aims to ensure three properties. First, the forecasts need to be unbiased predictors of future interest rates. Second, the error term should be a representation of the exogenous mis-estimation of market participants and not the result of incoming information between the forecast and the observed interest rate. Third, the effect of FG needs to be separated from other tools of unconventional monetary policy. In the subsequent sections we describe our data handling and Table 7 provides some more details of the employed data series.

### 4.4.1 Definition of the Error Term

Regarding the predictor of interest rates, our analysis refers to market based forward rates instead of survey forecasts. The main advantages of the market based rate is higher availability of different maturities and higher frequency coupled with the economic relevance of the decision behind these estimates. We choose the OIS over the Euribor for mainly three reasons [see Table 7]: First, the OIS is a secured contract between two financial market participants and has no counterparty credit risk, whereas Euribor rates incorporate a risk premium given their unsecured nature. While spread levels between both types of rates remain relatively constant for most of the periods, there have been sharp increases of the Euribor during times of distress due to additional risk factors (Schrimpf and Sushko, 2019). Second, the OIS is a truly market-determined rate while the Euribor is determined by selected financial institutions.<sup>54</sup> Third, the LIBOR scandal<sup>55</sup> gave rise to more trading activity in OIS which increases the reliability and the significance of available data collections.

---

<sup>54</sup> Data for the OIS is measured end of day and data for the EURIBOR is determined by a fixing once a day at 11 am UK time.

<sup>55</sup> Banks have manipulated quoted interest rates for financial gain as the EURIBOR has been the reference rate for numerous financial contracts.

**Table 7: Data Series Description**

Name	Source	Description
EUR/OIS 3 Month Zero Curve	BBG	SD0201Z 3M BLC2
EUR/OIS 3 Month Zero Curve 1 Year Forward	BBG	SD0201FC 3M1Y BLC
EUR/OIS 1 Year Zero Curve	BBG	SD0201Z 1Y BLC2
EUR/OIS 1 Year Zero Curve 1 Year Forward	BBG	SD0201FC 1Y1Y BLC
EUR/OIS 10 Year Zero Curve	BBG	SD0201Z 10Y BLC2
EUR/OIS 10 Year Zero Curve 1 Year Forward	BBG	SD0201FC 10Y1Y BLC
Real.GDP_yoy_sa	BBG	Real GDP year on year change
Inflation_yoy_sa	BBG	Inflation year on year change
Equity_Markets_yoy	BBG	Development of European Equity Markets
Vector_Risk_yoy	BBG	PCA constructed Risk Vector
BTP_yoy	BBG	Difference between the 10 year Bund and 10 year BTP
LTRO	ECB	Long term refinancing operations
ExcLiq	ECB	Excess Liquidity in the Euro Area
EAPP	ECB	Market Asset Purchase Programm
TLTRO	ECB	Targeted Long Term Refinancing Operations

Abbreviation: BBG = Bloomberg.

The sample includes daily data for the period between Q1 2010 to Q4 2018 available from Bloomberg. We define the prediction error term as follows:

$$y_{t1,Level} = OIS_{t0,t1,z} - i_{t1,z} \quad [8]$$

The level of the (one-year ahead) forecasting error,  $y_{t1,Level}$ , is defined as the difference between the forward OIS rate at  $t_0$  with a maturity of  $z$  effective from time  $t_1$  and the observation of the actual (realized) interest rate,  $i$ , at  $t_1$  for the same maturity  $z$ . In the baseline model, we cover the 1yr OIS forward for a maturity of 1 year. A positive error term indicates that the estimated interest rate turned out to be higher than the realized and vice versa. As a robustness test, we will further include the 1yr forecast for the 3m and the 10yr maturities. For the second perspective, the shape of the yield curve, we follow a similar logic:

$$y_{t1,Curve} = (OIS_{t0,t1,z2} - OIS_{t0,t1,z1}) - (i_{t1,z2} - i_{t1,z1}) \quad [9]$$

The forecast of the slope is the difference between the forward OIS with the long maturity  $z_2$  and the forward OIS with the short maturity  $z_1$  (the first difference element in eq. [9]). This implicit slope is compared to the actual realization of the slope represented by the difference between the observed interest rates,  $i$ , of the maturities  $z_2$  and  $z_1$  at time  $t_1$  (second difference element in eq. [9]). This results in the one year ahead forecast error for the slope of the yield curve,  $y_{Curve}$ . Our baseline model looks at the difference between ( $z_2 =$ ) 10yr and ( $z_1 =$ ) 3m maturities given its role as the most important indicator of the business cycle. A positive value

of the forecast error indicates that markets expected the yield curve to be steeper than its subsequent realization turns out to be. Our robustness test extends this perspective to the sub-segments, the slope between the 1yr and 3m maturity and the 10yr and the 1yr maturity.

#### ***4.4.2 Purging the Error Term from External Influences***

As our intent is to measure the impact of FG on interest rate predictability, we purge the prediction error term from influences that are due to information that occurred between the date of the forecast and the actual realization of the interest rate one year ahead. We follow a procedure suggested by Hatzius et al. (2010) and estimate a regression with the forecast error as the dependent variable to purge it from a number of factors that could substantially affect the quality of the prediction. Our assumption is that the residual of this regression represents the prediction error which is uncorrelated to the updated information set. We regress

$$y = \alpha + \sum_{i=1}^n \beta_i * v_i + \varepsilon \quad [10]$$

where  $y$  represents the prediction error of the interest rate level or curve as defined in the previous section in eqs [8] and [9], respectively. We include a constant,  $\alpha$ , which represents the term premium inherent in interest rate forecasts as well as the asymmetric nature of the future path of interest rates at the ZLB. The vector  $v_i$  contains a number of variables,  $i$ , that reflect macroeconomic dynamics, developments on financial markets and general risk sentiment. The regressors includes the 1yr growth rates of real GDP and core inflation to capture fundamental developments in the economy that have an effect on central banks and market participants. The Bund-BTP spread represents the difference between the 10yr generic German government bond yield and the equivalent yield of government bonds of Italy to capture periods of financial market fragmentation within the euro area. In addition, we include the 1yr return of the EuroSTOXX50 as well as a risk vector, which combines various measures of volatility via principal component analysis (equity markets, interest rate volatility, commodities). Our main focus is residual  $\varepsilon$  which represents our purged forecast prediction error and the relevant variable for the subsequent steps of the analysis.

#### ***4.4.3 Definition of Forward Guidance***

The third step of the analysis assesses the impact of central bank policy on the purged forecast error. To quantify the impact, we look at the absolute error term and estimate a regression containing a dummy variable that takes the value of 1 since the official introduction of FG on

July 4<sup>th</sup>, 2013. To distinguish between FG and additional monetary policy tools, we further include four control variables, which represent the level of different monetary operations the ECB conducted over this time period.

$$y_{purged} = \alpha + \sum_{i=1}^n \beta_i * FG_i + \sum_{i=1}^n \gamma_i * \begin{bmatrix} LTRO \\ TLTRO \\ EAPP \\ ExcLiq \end{bmatrix}_i + \varepsilon \quad [11]$$

$y_{purged}$  reflects the error term that is purged of macroeconomic influences. FG represents the dummy variable taking the value of 1 or 0. The control vector contains four variables<sup>56</sup>: First, the ECB Balance Sheet Long Term Refinancing Operations (LTRO) was designed to ease refinancing problems of peripheral countries during the height of the European peripheral crisis under strict conditionality. Second, the Targeted Longer-Term Refinancing Operations (TLTROs) were introduced to revive credit growth and help the economy to escape the liquidity trap. Third, the Expanded Asset Purchases programme (EAPP) was a broad-based attempt to revive different monetary transmission channels through lowering refinancing conditions across different markets. In addition, we included an aggregate measure of excess liquidity (ExcLiq) in the market as the fourth control variable as the ECB has been lending unlimited amounts of liquidity to banks in response to the financial crisis. Given the ambiguity of the start of FG, the analysis tests for an additional potential starting date in the robustness section. On July 26<sup>th</sup>, 2012, Mario Draghi affirmed markets that the ECB “*will do whatever it takes*” to preserve the euro, which represent a holistic form of FG covering not only interest rates but the full plethora of central bank tools (Draghi 2012).

#### 4.5 The Effects of Forwards Guidance

This section decomposes the prediction error of interest rates and the yield curve stepwise from the observable to the unobservable components. In a first step, we provide a qualitative description of the observable forecast error over the sample period. In the subsequent step, we account for the incomplete set of information that financial market participants face by purging the original error term of macroeconomic and financial information coming in between the date of the forecast and the actual realization as described above. In a third step, we quantify the effect of FG on forecast accuracy while controlling for other monetary policy actions.

---

<sup>56</sup> The control variables are represented by their actual volume and not as dummy variables.

#### ***4.5.1 The Observable Forecast Error***

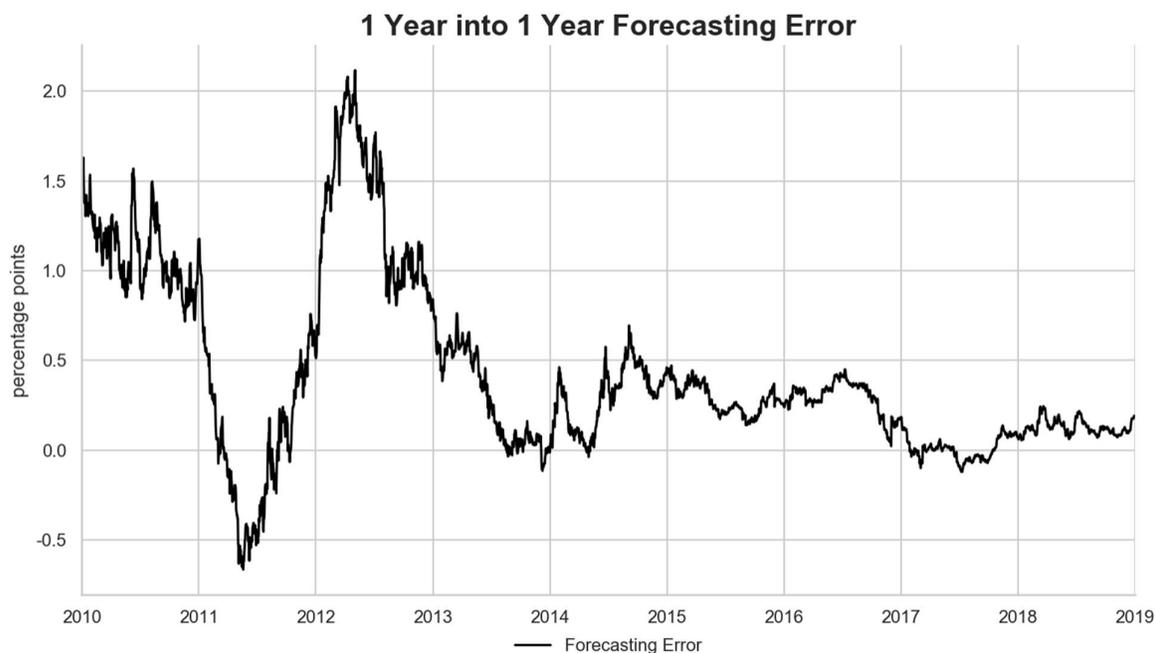
The traditional (i.e., representative) interest rate path during an economic expansion can be described by incremental increases of the short-term interest rate followed by a pause during the more advanced stages of the economic cycle. Subsequently, a faster decrease of interest rates towards the ZLB reverses the upward trend as economic conditions begin to deteriorate. After remaining at a low interest rate level, the central bank tends to initiate the lift-off when data suggests sufficient confidence in a firming of economic momentum after an economic downturn.

The sample period of this study, however, does not exhibit the traditional dynamics of an economic recovery. The period under consideration can be categorized into different sub-periods beginning with an initial recovery phase in the aftermath of the GFC. As an economic recession and a financial crisis coincided, the extent of the GDP shortfall during the GFC was larger than in previous recessions and it took the ECB about three years to pursue a rate-liftoff with two hikes in 2011. These interest rate increases provided the monetary prelude to the double-dip recession that hit the euro area in 2012 with a regional focus in the European periphery. The ECB responded with a reversal of monetary policy, and steered rates towards the ZLB for the remainder of the sample period in an attempt to stimulate economic activity in the wake of a liquidity trap. In the following period, the euro area experienced sluggish economic growth dynamics between 2013 until 2016 with a temporary pick-up of credit growth and investment in 2017. Despite a gradual normalization of economic activity, monetary policy did not return to the traditional interest rate path but referred to a variety of unconventional monetary measures.

The forecast error term of the interest rate level for 1yr maturities of the OIS contract one year into the future picks up the economic volatility in the first half of the sample period and yields a consistent positive term premium [see Figure 17]. During the first period in the immediate aftermath of the GFC, markets have overestimated the pace of interest rate normalization by the central bank. When the ECB decided to hike rates twice in 2011, the error term eventually disappeared for a couple of months until the European peripheral sovereign debt crisis unfolded. Following the reversal of the hawkish mistake by the central bank and subsequent interest rates cuts, the market finally began to price in a lower trajectory of future interest rate policy. The average forecasting error for the period between Q1 2013 and Q4 2017 drops down to 0.22pp from 0.69pp in the earlier period. The observation of a consistent term premium displayed by the positive error term can be explained by the asymmetric nature of the future trajectory at the ZLB. While room for further interest rate

compression is limited, it is rational for markets to price in a certain probability that the ECB may reverse course. Goodhart and Lim (2011) show that interest rate forecasts are biased due to the state of the business cycle. Once a central bank has started hiking interest rates during a recovery, markets underestimate the pace of rate increases while the reverse holds true for an economic contraction and a falling interest rate environment. A possible explanation could be that turning points in interest rate policy are inherently difficult to predict. In the particular case of the last decade, the turning point would be the start of the rate hike cycle which is priced in as a tail-event through the persistent term premium.

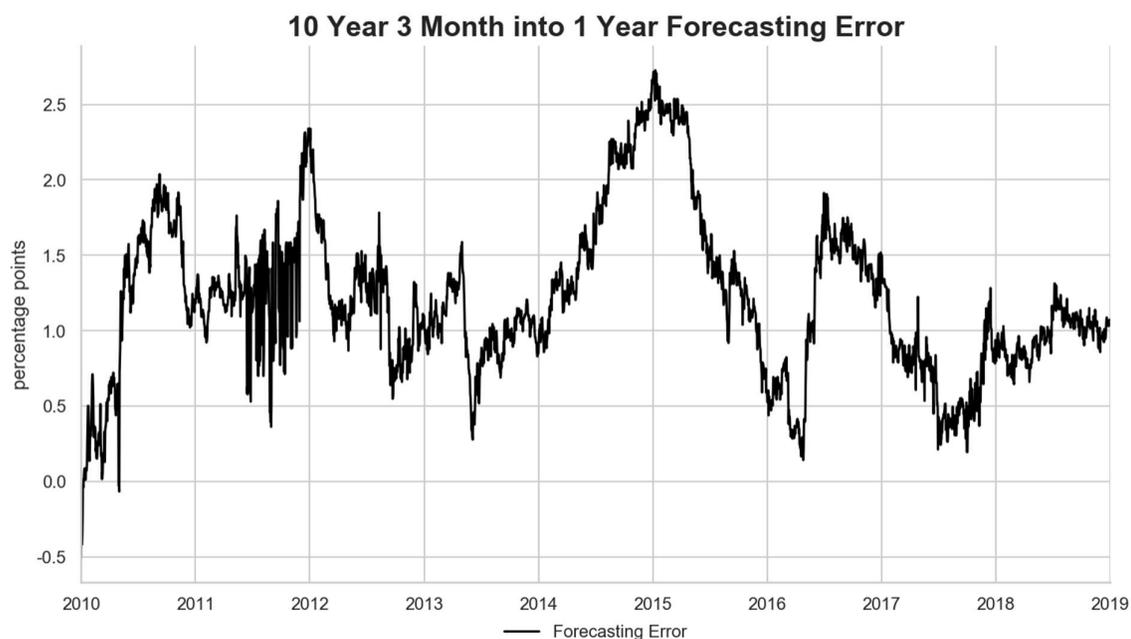
**Figure 17: Forecasting Error of the Interest Rate Level**



Regarding the market’s forecasting ability on the slope of the interest rate curve, our analysis focuses on the difference between interest rates of 10yr and 3m maturities one year ahead [see Figure 18]. Over nearly the whole sample period, markets have constantly overestimated the steepness of the curve by 1.21pp on average. While the error term over the first four years remains rather range-bound after surging from negative territory in the first quarter in 2010, we can observe two distinct local maxima of the error term during the period between Q3 2014 and Q2 2015 (2.72pp) and Q3 and Q4 2016 (1.91pp), where markets significantly overestimated the slope of the curve. This observation stands in contrast to the previous analysis on the forecast error of the interest rate level, where the error term dropped

during the later years. When decomposing the drivers of this structural, positive deviation of the curve forecast, data indicates that markets have not correctly estimated the structural decline of the 10yr interest rate. From Q2 2012 onwards, the 10yr maturity declined from levels around 2.5% to an absolute low in Q2 2017 of 0.86%. For a brief period at the beginning in 2015, both forecasts and actual rates had been aligned. This was driven by recessionary fears earlier that year which translated into a flattening of yield curve expectations. As concerns about future economic growth turned out to be overstated, the 10yr rate increased in the second half of 2015, which reduced the positive forecast error. The observations for the sample period underline that markets were surprised by the flattening of the interest rate curve over the last four years.

**Figure 18: Forecasting Error of the Interest Rate Yield Curve**



#### ***4.5.2 Assessment of the Exogenous Prediction Error***

To extract the exogenous component of the forecast error unrelated to the business cycle, we regress the forecast error on a vector containing information about economic dynamics, financial market data and risk sentiment as shown in eq. [10]. We interpret the error term of the regression as the purified prediction error. Results for the level forecasts suggest that all regressors are highly significant and explain 58% of the variation of the purged error term [see Table 8].

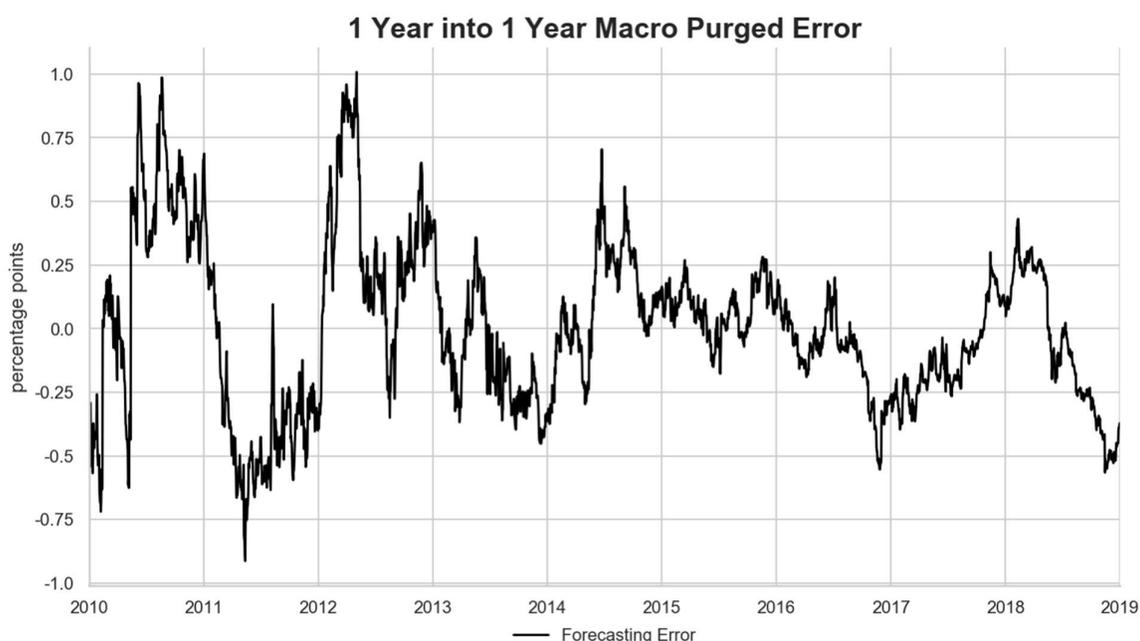
**Table 8: Regression to Purge the Forecast Error (Interest Rate Level) from External Factors**

	coef	std err	t	P> t	[0.025	0.975]
const	1.0338	0.027	38.969	0.000	0.982	1.086
Real_GDP_yoy_sa	-0.2961	0.519	-57.061	0.000	-0.3063	-0.2859
Inflation_yoy_sa	-0.2068	1.904	-10.865	0.000	-0.2441	-0.1694
Equity_Markets_yoy	-0.7884	0.055	-14.267	0.000	-0.897	-0.680
Vector_Risk_yoy	-0.1036	0.008	-12.406	0.000	-0.120	-0.087
BTP_yoy	0.2080	0.006	35.251	0.000	0.196	0.220
Dep. Variable:	FE_1Y	R-squared:	0.584			
Model:	OLS	Adj. R-squared:	0.584			
No. Observations:	3287	AIC:	1881.			
Df Residuals:	3281	BIC:	1918.			

Abbreviations: yoy = year-on-year; sa = seasonally-annualized;

The variables that describe a sizeable portion of the observed variation are real GDP, core inflation and the Bund-BTP spread. The coefficients for the year-on-year growth of (seasonally adjusted) real GDP and (seasonally adjusted) core inflation are negative, which associates an increase of these variables with a negative forecast error. Hence, positive GDP data and increasing inflation push up actual rates beyond what was expected at the time of the 1yr ahead forecast. While 1pp GDP growth has an impact of -0.3pp on the forecast error, 1pp of inflation growth exerts downward pressure of -0.21pp. Results reveal a positive coefficient for the 1yr change of the Bund-BTP spread, indicating that a widening of the perceived risk difference between 10yr German and Italian government bonds coincides with an overshooting of rates expectations. As fears about the European periphery were emerging, the absolute level of rates in the euro area declined to a degree not expected by forecasts. This translates into a positive forecast error of 0.2pp for a 1pp Bund-BTP spread. The coefficients for the equity and the risk vector are also significant, however, with a lower impact. The intercept of the regression stands at 1.03pp which we interpret as the sum of the term premium and the asymmetric risk of an increase in rates at the ZLB when controlling for the impact of the business cycle on the forecast error. The purified prediction error displayed in Figure 19 has a correlation of 0.64 with the original time series and has largely eliminated the dominating impact of the business cycle on the raw forecast error term.

**Figure 19: Purged Forecasting Error of the Interest Rate Level**



Regression results for eq. [10] using the yield curve forecast displayed in Table 9 show that regressors are significant except for the Bund-BTP spread (only significant at the 10% level). The amount of variation that is explained by economic and financial data decreases to 14%.

**Table 9: Regression to Purge the Forecast Error (Interest Rate Curve) from External Factors**

	coef	std err	t	P> t	[0.025	0.975]
const	1.6694	0.041	41.160	0.000	1.590	1.749
Real_GDP_yoy_sa	0.0392	0.793	4.948	0.000	0.0237	0.0548
Inflation_yoy_sa	-0.4143	2.910	-14.239	0.000	-0.4714	-0.3573
Equity_Markets_yoy	-0.5059	0.084	-5.988	0.000	-0.672	-0.340
Vector_Risk_yoy	0.1104	0.013	8.653	0.000	0.085	0.135
BTP_yoy	0.0155	0.009	1.718	0.086	-0.002	0.033
Dep. Variable:	FE_3M10Y		R-squared:		0.144	
Model:	OLS		Adj. R-squared:		0.142	
No. Observations:	3287		AIC:		4698.	
Df Residuals:	3281		BIC:		4735.	

In line with the analysis of the level forecast error, real GDP and core inflation are the variables that are driving the prediction error. However, the signs of their coefficients are different with real GDP being associated with a positive forecast error and core inflation leading to a lower and in absolute terms much larger forecast error. An increase of core inflation by 1pp is decreasing the prediction error by 0.41pp as the actual curve becomes

steeper and closer to what was anticipated. Inflation exerts a stronger impact on 10yr rates yielding a prediction error of -0.61pp as compared to -0.27pp for the 3m rate. In contrast, a positive change in real GDP by 1pp increases the prediction error on the interest rate curve by 0.04pp. These results reflect that core inflation seems to drive the forecast error for longer-dated rates while economic growth is more relevant for forecasts of the shorter-dated part of the interest rate curve. The purified forecast error is highly correlated (0.93) with original time series. As can be observed in Figure 20, financial markets are still caught by surprise about the degree of curve flattening indicated through the peaks between 2015 and 2016.

**Figure 20: Purged Forecasting Error of the Interest Rate Yield Curve**



#### ***4.5.3 Quantification of the Effect of Forward Guidance on the Prediction Error***

During the period of unconventional monetary policy, the ECB gradually strengthened their grip on the interest rate curve through an expanded monetary toolkit. The official introduction of FG on July 4<sup>th</sup>, 2013 adds to a series of new and non-standard monetary instruments that have impacted financial markets and corresponding forecasts. Not only does the actual start date of FG leave room for discussion, it is the plethora of newly introduced central bank measures and the corresponding communication policy that makes it inherently difficult to isolate and quantify the impact of FG on interest rate predictability. Hence, this section starts with a parsimonious definition of a dummy variable reflecting the official start of FG and widens the scope of analysis to include monetary policy control variables.

Table 10 displays the results of regressing the purged error term on the FG dummy and a constant only, which represents a reduced form of eq. [11] without the vector of controls. Results of the baseline specification reveal that during the regime of FG starting July 4<sup>th</sup> 2013, the forecast error of interest rate levels (FE\_1Y) has decreased (column 1) while the forecast error of the slope of the (3 months to 10 year) yield curve (FE\_3M10Y) has increased (column 2).

**Table 10: Regression of the Purged Forecast Error on FG**

	FE_1Y	FE_3M10Y	FE_3M1Y	FE_1Y10Y
const	0.3694*** (0.0049)	0.3105*** (0.0089)	0.2583*** (0.0038)	0.4291*** (0.0093)
FG_4_July_2013	-0.1889*** (0.0062)	0.0990*** (0.0114)	-0.1054*** (0.0048)	0.0303** (0.0119)
<b>Adj. R-squared</b>	0.2182	0.0221	0.127	0.002

*Notes: FE stands for the purged forecast error measured for the 1yr forecast horizon. FE followed by one number represents a level forecast for the respective maturity. FE followed by two numbers represents a slope forecast for respective maturities.*

*Significance Levels: \*1%, \*\* 5%, \*\*\*10%.*

Regarding the level forecasts, the coefficient of the FG dummy is highly significant and points to a reduction of the error term by 0.19pp. This finding lends support to our initial hypothesis that this new communication tool helped financial market participants to more accurately predict future interest rates. The FG regime has obviously succeeded in reducing the perceived probability of unexpected rate hikes given the asymmetric risk profile for interest rates at the ZLB. However, regarding the forecasts on the slope of the interest rate curve, results show an increase in the forecast error by 0.10pp (column 2). The decomposition of this observation into its two components, the forecast error of the 3m OIS contract and the 10yr OIS contract, shows that FG leads to a reduction of the forecast error term for the shorter horizon (column 3) and a slight increase for the longer maturity (column 4). While monetary policy has succeeded in guiding market expectations of shorter term maturities, the structural decline of the 10yr interest rate was not anticipated by financial markets participants. This finding indicates that the ECB's goal to suppress long-term refinancing conditions was achieved at the cost of surprising markets on the path of long-term yields.

To further refine the perspectives on the central bank regime under FG, this section introduces additional control variables that represent major monetary policy operations over the sample period as specified in the full form of eq. [11]. The regression results are shown in Table 11. The control variables we included are the following: LTRO represents the

unconditional long-term refinancing operations of the European Central Bank; ExcLiq is the liquidity provided by the central bank system; EAPP captures monthly asset purchases conducted by the ECB and TLTRO stands for the targeted long-term refinancing operations of the ECB.

**Table 11: Regression of the Purged Forecast Error on FG and Control Variables**

	FE_1Y	FE_3M10Y
const	0.4946*** (0.0117)	0.4565*** (0.0218)
FG_4_July_2013	-0.1685*** (0.0083)	0.1309*** (0.0154)
LTRO	-0.2739*** (0.0195)	-0.1599*** (0.0362)
ExcLiq	0.1673*** (0.0100)	-0.1265*** (0.0187)
EAPP	-2.0501*** (0.1425)	-0.1923 (0.2647)
TLTRO	-0.4858*** (0.0470)	0.3132*** (0.0874)
<b>Adj. R-squared</b>	0.293	0.089

*Notes: FE stands for the purged forecast error measured for the 1yr forecast horizon. FE followed by one number represents a level forecast for the respective maturity. FE followed by two numbers represents a slope forecast for respective maturities.*

*Significance Levels: \*1%, \*\* 5%, \*\*\*10%.*

Regarding the forecast error for the 1y1y OIS (FE\_1Y), FG remains significant in narrowing the prediction error by 0.17pp (column 1). This represent a decline by two basis points as compared to the specification without control variables. The latter are all highly significant with an overall model fit improving to 0.29. The intercept of the regression stands at 0.50pp which we interpret as the structural absolute prediction error if we account for both FG and other monetary policy actions. As this value is 0.15pp larger than the average of the absolute purged prediction error, we infer that the sum of monetary policy measures significantly compresses the interest rate forecast error. On the prediction error of the slope forecasts (FE\_3M10Y), the fully specified baseline model suggests that FG increases the forecast error by 0.13pp yielding a model fit of 0.089 (column 2). This effect is stronger than considering the slope forecast in isolation (by +0.10pp). Hence, the monetary control variables seem to have a dampening effect on the absolute error term, where FG is the main reason for markets underestimating the flattening of the interest rate curve. The intercept of 0.46pp reflects again the structural error term that markets exhibit in their forecasts on the slope of the interest rate curve.

## 4.6 Robustness Tests

This section considers different specifications of the baseline model and extends the analysis across different maturities. For the level forecast, we vary the maturity of the OIS contract to 3 months (FE\_3M) and 10 years (FE\_10Y). Regarding the slope of the yield curve, we analyze the slope between the 1y and the 3m maturity (FE\_3M1Y) and the 10y and 1y attachment points (FE\_1Y10Y).<sup>57</sup> To address the question whether the official start date of FG marks the unambiguous beginning of a new communication regime, we estimate the baseline regression with an alternative dummy variable that represents a key speech of Mario Draghi on July 26<sup>th</sup>, 2012, where he reiterates the ECB's willingness “*to do whatever it takes*” to preserve the euro.

### 4.6.1 Prediction Error for the Level and Slope Forecast with Different Maturities

We first purged the forecast errors as before.<sup>58</sup> As displayed in Table 12, we find that unconventional monetary policy has a higher overall explanatory power for interest level forecasts at shorter maturities than for the long term. While the adjusted  $R^2$  indicates a model fit of 0.26 for the 3m OIS contract, this statistic increases slightly to 0.293 for the 1yr OIS contract [Table 11, column 1] and eventually drops to 0.07 for the 10yr horizon [Table 12, column 2]. It is a common finding that central bank policies have a greater impact on the front-end of the interest rate curve than for longer maturities.

As a stark contrast to the baseline specification, FG actually increases the absolute forecast error for the 10yr OIS contract (FE\_10Y) by 0.16pp while the effect on the 3m OIS contract (FE\_3M) is rather insignificant in size. We infer that FG has fostered interest rate predictability for interest rates at shorter maturities but significantly decreased predictability at the long-end of the interest rate curve. The explanatory power of unconventional monetary policy on the absolute forecast error of the slope of the yield curve also declines with increasing maturity. The model on the yield curve at the front-end indicates an adjusted  $R^2$  of 0.23 for the 1y-3m attachment points (FE\_3M1Y), while variation in the forecast error of the 10y-1y slope (FE\_1Y10Y) is explained to a lesser degree by monetary policy (adjusted  $R^2$  of 0.08). The positive effect of FG on the forecast error of the baseline model (0.13pp) stems solely from the long-end of the curve that points to an increase of the prediction error of 0.16pp as can be seen in Table 11 in combination with Table 12. These findings highlight that

---

<sup>57</sup> We do not consider interest rate forecasts greater than one year given the increasing impact of other external factors on interest rate predictability.

<sup>58</sup> For the sake of brevity, we do not report the results explicitly, but they are available upon request. As before, almost all chosen control variables are statistically significant.

the source of the forecast error for the slope is the strong an unexpected decrease of longer-term maturities.

**Table 12: Regression of the Purged Forecast Error across different Maturities**

	FE_3M	FE_10Y	FE_3M1Y	FE_1Y10Y
const	0.1497*** (0.0088)	0.3685*** (0.0228)	0.2790*** (0.0069)	0.4400*** (0.0201)
FG_4_July_2013	-0.0224*** (0.0062)	0.1554*** (0.0161)	-0.0968*** (0.0048)	0.0390*** (0.0142)
LTRO	0.1471*** (0.0145)	0.1873*** (0.0379)	-0.1677*** (0.0114)	-0.0739** (0.0334)
ExcLiq	0.0373*** (0.0075)	-0.1914*** (0.0195)	0.0413*** (0.0059)	-0.1766*** (0.0172)
EAPP	-1.1611*** (0.1063)	-1.0842*** (0.2770)	0.1016 (0.0834)	0.4813** (0.2442)
TLTRO	-0.3968*** (0.0351)	0.3767*** (0.0915)	-0.2546*** (0.0275)	0.6118*** (0.0806)
<b>Adj. R-squared</b>	0.262	0.066	0.225	0.080

Notes: FE stands for the purged forecast error measured for the 1yr forecast horizon. FE followed by one number represents a level forecast for the respective maturity. FE followed by two numbers represents a slope forecast for respective maturities.

Significance Levels: \*1%, \*\* 5%, \*\*\*10%.

#### 4.6.2 Alternative Starting Date of FG

As displayed in Table 13, with Draghi's "whatever it takes speech" as the alternative beginning of FG (FG\_26\_July\_2012), we can observe an increase of the model fit to 0.36 for the 1y maturity.

**Table 13: Regression of the Purged Forecast Error with alternative FG Date**

	FE_1Y	FE_3M10Y	FE_3M	FE_10Y	FE_3M1Y	FE_1Y10Y
const	0.4379*** (0.0102)	0.5115*** (0.0200)	0.1537*** (0.0078)	0.4503*** (0.0211)	0.2444*** (0.0061)	0.4547*** (0.0184)
FG_26_July_2012	-0.2119*** (0.0074)	0.1149*** (0.0145)	-0.0806*** (0.0056)	0.0609*** (0.0153)	-0.1124*** (0.0044)	0.0417*** (0.0133)
LTRO	-0.0767*** (0.0185)	-0.2870*** (0.0362)	0.2007*** (0.0141)	0.0761** (0.0383)	-0.0593*** (0.0110)	-0.1157*** (0.0333)
ExcLiq	0.1263*** (0.0095)	-0.0999*** (0.0187)	0.0262*** (0.0073)	-0.1680*** (0.0197)	0.0187*** (0.0057)	-0.1679*** (0.0172)
EAPP	-1.6096*** (0.1363)	-0.1870 (0.2673)	-0.7358*** (0.1042)	-0.5494* (0.2826)	0.2898*** (0.0814)	0.4313* (0.2462)
TLTRO	-0.4497*** (0.0444)	0.3394*** (0.0871)	-0.3348*** (0.0340)	0.4905*** (0.0921)	-0.2440*** (0.0265)	0.6116*** (0.0802)
<b>Adj. R-squared</b>	0.364	0.087	0.302	0.044	0.275	0.081

Notes: FE stands for the purged forecast error measured for the 1yr forecast horizon. FE followed by one number represents a level forecast for the respective maturity. FE followed by two numbers represents a slope forecast for respective maturities. Significance Levels: \*1%, \*\* 5%, \*\*\*10%.

The forecast error of the level (FE\_1Y) decreases to -0.21pp compared to a negative impact of -0.17pp [Table 11] in the baseline model. Results for the forecast of the slope of the yield curve show similar characteristics with a highly significant coefficient which indicates that FG leads to a widening of the prediction error by 0.12pp (compared to 0.13pp in the baseline). As can be seen from the columns 3-6 of Table 13, the results as well as the overall fit for the alternative maturities also improves. Hence, the ECB's the announcement of unconditional support of the euro within its mandate marks a significant event that has helped to improve interest rate predictability.

#### **4.7 Concluding Remarks on the Effect of Forward Guidance**

This chapter analyzes the impact of ECB's FG on the forecast error of financial markets participants regarding the interest rate level and the slope of the yield curve. To account for external factors other than the exogenous quality of interest rate predictions, we purge the error term of macroeconomic and financial variables and then control the absolute, purged forecast error for instances of unconventional monetary policy.

We find that the introduction of FG by the ECB on July 4<sup>th</sup>, 2013 leads to a decline in the prediction error of the interest rate level by 0.17pp for the 1yr maturity for the 1yr forecasting horizon. While the effect is negligible for 3m maturities, the forecasting error of interest rates of 10yr actually increases through the introduction of FG by 0.16pp on the back of the decline of the 10yr interest rate which caught markets by surprise. Hence, the ECB has succeeded in lowering long-term refinancing conditions at the price of lower interest rate predictability for longer dated maturities during the time of FG. This finding also manifests itself in the results for the prediction error of the slope of the interest rate curve. Measured as the difference between the 10yr and the 3m maturities, forecasts of the interest rate curve become less accurate through the introduction of FG and increase by 0.13pp on an absolute basis on the back of the unanticipated fall of the 10yr rate. We further find that a different specification of FG including the "whatever it takes" speech by Mario Draghi results in an even stronger effect than the ECB's official announcement date. While the accuracy of the predictions on the interest rate level improve by two additional basis points, the forecasts on the slope of the yield curve worsen by another two basis points.

Overall, the ECB's communication policy has strong and observable effects on the forecast error of market participants. The fact that FG leads to an improved predictability for shorter maturities also implies a partial stabilization effect on financial markets. Further, if financial market participants themselves observe that FG has become a significant tool for

steering interest rates further out on the maturity spectrum, the credibility of monetary policy and thus its effectiveness improves. For longer maturities, however, signals of the ECB have not been accurately reflected in the forecasts of financial market participants which leaves room for improved communication (and understanding) going forward.

## 5. Conclusion

In order to navigate in uncharted waters with an expanded monetary policy toolkit, the ECB is required to closely monitor business cycle dynamics and the effectiveness of its new policy instruments. To shed light on both areas, this dissertation examines ways to assess the recession probability in the euro area, the nature of uncertainty among consumers, corporations and financial markets as well as the effectiveness of forward guidance on interest rate predictability.

With respect to predicting recessions in the euro area, we find that the yield curve largely lost its forecasting ability as the ECB hit the ZLB earlier this decade. To remove the downward rigidity of short-term rates, we suggest a modified version of the term spread which uses the ‘shadow policy rate’, rather than the 3-month rate, as the front leg of the spread. The analysis, however, also finds that there are alternative indicators of recession (e.g. real money growth, the PMI) that outperform even this improved term spread. We therefore suggest looking at a range of measures to assess the recession probability in the euro area rather than being overly focused on the shape of the yield curve. In a first submodel, the creation of monetary transmission channels yields the strongest improvements for the categories of industrial data, refinancing variables and preference for risk by eliminating idiosyncratic fluctuations. Results for a second submodel suggest bivariate combinations to perform significantly better than the univariate specification reducing the risk of overfitting. Considering the deviation from the HP trend in a third submodel achieves significant improvements for indicators in the run-up to the recession of 2008-2009 which can be characterized by signs of overheating. Regarding different forecasting horizons, we observe that sentiment indicators and industrial data improve significantly for shorter time horizons, whereas corporate spreads and the euro area peripheral sovereign bond spread underline their leading character vis-à-vis the business cycle given a remarkable performance over longer forecasting horizon.

Regarding the shape of uncertainty across consumers, corporations and financial markets, we find that all four moments of the uncertainty distribution are negatively correlated with GDP growth with correlation coefficients ranging from -0.77 to -0.05 in increasing order. The qualitative assessment of the first moment lends support to the idea that point estimates of the confidence level are strongly representative of business cycle dynamics. The second moment of uncertainty is also strongly negatively correlated with GDP and provides insights into how unanimous economic agents are about their point estimate. The analysis of the third moment reveals that positive skewness is associated with negative growth while the fourth moment does not allow for firm conclusions about its relationship with the business cycle. By quantifying the impact of uncertainty, impulse response functions suggest that a one standard deviation shock to the innovations of the first moment of uncertainty leads to an initial cumulative decline in GDP of -1.1% over the first two years which is reduced by half due to an overshoot of GDP growth over the subsequent years. This causes a permanent effect on the level of GDP, but only a temporary effect on the growth rate. By decomposing the shock on the first moment of uncertainty, we can attribute the largest impact to the corporate sector and observe the effect of financial markets being equally strong in the beginning but fading much quicker. We conclude that augmenting a GDP forecasting model by the first and second moment of uncertainty clearly improves overall forecast accuracy.

By inspecting the effectiveness of the ECB's FG, we find that its introduction on July 4<sup>th</sup>, 2013 leads to a decline in the prediction error of the interest rate level by 0.17pp for the 1yr maturity for the 1yr forecasting horizon. While the effect is negligible for 3m maturities, the forecasting error of the 10yr maturities actually increases through the introduction of FG by 0.16pp on the back of the decline of the 10yr interest rate which caught markets by surprise. Hence, the ECB has succeeded in lowering long-term refinancing conditions at the price of lower interest rate predictability for longer dated maturities during the time of FG. This finding also manifests itself in the results for the prediction error of the slope of the interest rate curve. Measured as the difference between the 10yr and the 3m maturities, forecasts of the interest rate curve become less accurate through the introduction of FG and increase by 0.13pp on an absolute basis on the back of the unanticipated fall of the 10yr rate. We further find that a different specification of FG including the "whatever it takes" speech by Mario Draghi results in an even stronger effect than the ECB's official announcement date.

Overall, results of this dissertation indicate that a change in the economic landscape after the GFC with short-term interest rates pinned down at the ZLB requires the ECB to review and refine their ways on how to assess the stance of the economy. The research

suggests revised measures to analyze the later stages of the economic cycle, a more granular view of the transmission channel of aggregate uncertainty and provides a first assessment of the newly introduced monetary policy tool of FG.

## References

- Abel, A. (1983): “Optimal investment under uncertainty”, *The American Economic Review*, 73(1), 228–233.
- Adrian, T. / Brunnermeier, M. K. (2016): “CoVar”, *American Economic Review*, 106(7), 1705-1741.
- Alessi, L. / Detken, C. (2009): “Real time early warning indicators for costly asset price boom/bust cycles. A role for global liquidity”, ECB Working Paper Series, no. 1039.
- Andersson, M. / Hofmann, B. (2009): “Gauging the effectiveness of quantitative forward guidance: Evidence from three inflation targeters”, European Central Bank, Working Paper Series, no. 1098.
- Andrade, P. / Ferroni, F. (2016): “Delphic and Odyssean monetary policy shocks: Evidence from the euro area”, School of Economics University of Surrey Discussion Papers, no. 1216.
- Arellano, C. / Bai, Y / Kehoe, P. (2011): “Financial markets and fluctuations in uncertainty”, Federal Reserve Bank of Minneapolis Research Department Staff Report.
- Bachmann, R. / Elstner, S. / Sims, E. R. (2013): “Uncertainty and economic activity: Evidence from business survey data”, *American Economic Journal: Macroeconomics*, 5(2), 217-249.
- Baker, S. R. / Bloom, N. / Davis, S. J. (2016): “Measuring economic policy uncertainty”, *Quarterly Journal of Economics*, 131(4), 1593-1636.
- Becker, T. / Smith, A. L. (2015): “Has forward guidance been effective?”, Federal Reserve Bank of Kansas City, *Economic Review*, 100(3), pp. 57-78.
- Bekaert, G. / Hoerova, M. / Duca, M. L. (2013): “Risk, uncertainty and monetary policy”, European Central Bank Working Paper Series, no. 1565.
- Bellégo, C. / Ferrara, L. (2009): “Forecasting euro area recessions using time-varying binary response models for financial variables”, Document de travail, Banque de France, 259.
- Berge, T. J. / Jordà, Ò. (2011): “Evaluating the classification of economic activity into recessions and expansions”, *American Economic Journal: Macroeconomics* 3(2), 246-277.
- Bernanke, B.S. (1983): “Irreversibility, uncertainty, and cyclical investment”, *Quarterly Journal of Economics*, 97(1), 85-106.
- Bernhardt, D. / Campello, M. / Kutsoati, E. (2006): “Who herds?”, *Journal of Financial Economics*, 80(3), 657-675.
- Birdsall, T. G. / Peterson, W. W. (1953): “The theory of signal detectability: Part I. The general theory”, Electronic Defense Group, Technical Report 13.

- Borio, C. / McCauley, R. N. / McGuire, P. / Sushko, V. (2016): “Covered interest parity lost: understanding the cross-currency basis”, *BIS quarterly review: international banking and financial market developments*, 09/2016, 45-64.
- Caballero, R. J. (1991): “Earnings uncertainty and aggregate wealth accumulation”, *The American Economic Review*, 81(4), 859-871.
- Caggiano, G. / Castelnuovo, E. / Nodari, G. (2017): “Uncertainty and monetary policy in good and bad times”, *Reserve Bank of Australia Research Discussion Paper 2017-06*.
- Campbell, J. R. / Evans, C. L. / Fisher, J. D. M. / Justiniano, A. (2012): “Macroeconomic effects of Federal Reserve forward guidance,” *Brookings Papers on Economic Activity*, Spring, 1-54.
- Chauvet, M. / Potter, S. (2005): “Forecasting recessions using the yield curve”, *Journal of Forecasting*, 24(2), 77-103.
- Chen, Z. / Azhar, I. / Lai, H. (2008): “Forecasting the probability of U.S. recessions: a probit and dynamic factor modelling approach”, *The Canadian Journal of Economics*, 44(2), 651-672.
- Christelis, D. / Georgarakos, D. / Jappeli, T. / van Rooij, M. (2016): “Consumption uncertainty and precautionary saving”, *DNB Working Paper*, no. 496.
- Chow, G. C. (1960): “Tests of equality between sets of coefficients in two linear regressions”, *Econometrica*, 28, 591–605.
- Deaton, A. S. (1991): “Saving and liquidity constraints”, *Econometrica*, 59 (5), 1221-1248.
- Del Negro, M. / Giannoni, M. / Patterson, C. (2012): “The forward guidance puzzle”, *Federal Reserve Bank of New York, Staff Reports*, no. 574.
- Dovern, J. / Ziegler, C. (2008): “Predicting growth rates and recessions: Assessing US leading indicators under real-time conditions”, *Kiel Institute for the World Economy, Working Paper*, no.1397.
- Draghi, D. (2012): “Speech by Mario Draghi, President of the European Central Bank at the Global Investment Conference in London 26 July 2012”, Retrieved from: <https://www.ecb.europa.eu/press/key/date/2012/html/sp120726.en.html>
- Draghi, M. (2013): “Introductory statement to the press conference (with Q&A)”, Retrieved from <https://www.ecb.europa.eu/press/pressconf/2013/html/is130704.en.html>
- Draghi, M. (2014): “Introductory statement to the press conference (with Q&A) ”, Retrieved from <https://www.ecb.europa.eu/press/pressconf/2014/html/is140306.en.html>

- Dueker, M. J. (1997): “Strengthening the case for the yield curve as a predictor of U.S. recessions”, *St. Louis Fed Review* (Mar), 41-51.
- Dynan, K. E. (1993): “How prudent are consumers?”, *Journal of Political Economy*, 101(6), 1104-1113.
- ECB (2014): “The ECB’s Forward guidance”, *Monthly Bulletin* 04/2014, 65-73.
- Ergungor, O. E. (2016): “Recession probabilities”, *Economic Commentary Federal Reserve Bank of Cleveland* 2016, 1-6.
- Ernst, E. / Viegelahn, C. (2014): “Hiring uncertainty: A new labour market indicator”, Available under [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2411299](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2411299).
- Estrella, A. / Hardouvelis, G. A. (1991): “The term structure as a predictor of real economic activity”, *The Journal of Finance*, 46(2), 555-576.
- Fendel, R. / Mai, N. / Mohr, O. (2018): “Recession probabilities for the Euro area at the zero lower bound: challenges to the term spread and rise of alternatives”, *WHU Working Paper Series*, 18-04.
- Fendel, R. / Mai, N. / Mohr, O. (2019): “Predicting recessions using term spread at the zero lower bound: The case of the euro area”, available at <https://voxeu.org/article/predicting-recessions-using-term-spread-zero-lower-bound>.
- Fendel, R. / Mai, N. / Mohr, O. (2019): “The shape of euro area’s uncertainty: Its impact and predictive value on GDP”, *WHU Working Paper Series*, 19-01.
- Fendel, R. / Heins, J. / Mohr, O. (2019): “The effect of the ECB’s forward guidance on interest rate forecasts”, *WHU Working Paper Series*, 19-09.
- Fendel, R. / Neugebauer, F. / Niederhagen, N. (2017): “A note on the reactions of real yields to different types of forward guidance in the US”, *Economics Bulletin*, 37(4), 2703-2710.
- Ferreira, T. R. T. (2018): “Stock market cross-sectional skewness and business cycle fluctuations”, *International Finance Discussion Papers*, no. 1223.
- Fornari F. / Lemke, W. (2010): “Predicting recession probabilities with financial variables over multiple horizons”, *ECB Working Paper Series*, no. 1255.
- Gilchrist, S / Sim, J / Zakrajsek, E. (2014): “Uncertainty, financial frictions, and investment dynamics”, *NBER Working Paper Series*, no. 20038.
- Gilchrist, S. / Zakrajšek E. (2012): “Credit spreads and business cycle fluctuations”, *American Economic Review*, 102 (4), 1692-1720.

- Goodhart, C. / Lim, W. B. (2011): "Interest rate forecasts: A pathology", *International Journal of Central Banking*, 7(2), 135-171.
- Guvenen, F. / Karahan, K. / Ozkan, S. / Song, J. (2015): "What do data on millions of U.S. workers reveal about life-cycle earnings risk?", *Federal Reserve Bank of New York Staff Reports*, no. 710.
- Haddow, H. / Hare, C. / Hooley, J. / Shakir, T. (2013): "Macroeconomic uncertainty: What is it, how can we measure it and why does it matter?", *Bank of England Quarterly Bulletin*, 53(2), 100-109.
- Hahm, J. / Steigerwald, D. G. (1999): "Consumption adjustment under time-varying income uncertainty", *Review of Economics and Statistics*, 81 (1), 32-40.
- Haltmaier, J. (2008): "Predicting cycles in economic activity", *Board of Governors of the Federal Reserve System Working Paper Series*, no. 926.
- Hartman, R. (1972): "The effects of price and cost uncertainty on investment", *Journal of Economic Theory*, 5(2), 258-266.
- Hatzius, J. / Hooper, P. / Mishkin, F. S. / Schoenholtz, K. L. / Watson, M. W. (2010): "Financial conditions indexes: A fresh look after the financial crisis", *NBER Working Paper Series*, no. 16150.
- Hubert, P. / Labondance, F. (2018): "The effect of ECB forward guidance on the term structure of interest rates", *International Journal of Central Banking*, 14(5), 193-222.
- Jurado, K. / Ludvigson, S. C. / Ng, S. (2015): "Measuring Uncertainty", *American Economic Review*, 105(3), 1177-1216.
- Kaminsky, G. / Reinhart, C. (1999): "The twin crises: The causes of banking and balance-of-payments problems", *American Economic Review*, 89(3), 473-500.
- King, T. B. / Levin, A. T. / Perli, R. (2007): "Financial market perceptions of recession risk", Washington DC: Div. of Research & Statistics and Monetary Affairs, Federal Reserve Board, Finance and economics discussion series, 2007-57.
- Knight, F. H. (1921): "Risk, uncertainty, and profit", Boston, MA: Hart, Schaffner & Marx; Houghton Mifflin Company.
- Kool, C. J. M. / Thornton, D. L. (2015): "How effective is central bank forward guidance?", *Federal Reserve Bank of St. Louis Review*, 97(4), 303-22.
- Krippner, L. (2013): "Measuring the stance of monetary policy in zero lower bound environments", *Economics Letters*, 118(1), 135-38.

- Krippner, L. (2014): “Measuring the stance of monetary policy in conventional and unconventional environments,” Centre for Applied Macroeconomic Analysis Working Paper Series, 6/2014.
- Krugman, P. R. (1998): “It's baaack: Japan's slump and the return of the liquidity trap”, Brookings Papers on Economic Activity 1998, Issue 2, 137-187.
- Kuttner, K. (2001): “Monetary policy surprises and interest rates: Evidence from the Fed funds futures market”, *Journal of Monetary Economics*, 47 (3), 523–44.
- Laubach, T / Williams, J. C. (2015): “Measuring the natural rate of interest redux”, Federal Reserve Bank of San Francisco Working Paper Series, 2015-16.
- Leduc, S. / Liu, Z. (2016): “Uncertainty shocks are aggregate demand shocks”, *Journal of Monetary Economics*, 82(C), 20-35.
- Levanon, G. / Manini, J. C. / Ozyildirim, A. / Schaitkin, B. / Tanchua, J. (2011): “Using a leading credit index to predict turning points in the U.S. business cycle”, The Conference Board, Economics Program Working Paper Series, 11(5).
- Liu, W. / Moench, E. (2014): “What predicts U.S. recessions?”, Federal Reserve Bank of New York Staff Reports Staff Report, no. 691.
- Madsen, J. B. / McAleer, M. (2000): “Direct tests of the permanent income hypothesis under uncertainty, inflationary expectations and liquidity constraints”, *Journal of Macroeconomics*, 22(2), 229-252.
- McDonald, R. / Siegel, D. (1986): “The value of waiting to invest”, *Quarterly Journal of Economics*, 101(4), 707–728.
- Mincer, J. / Zarnowitz, V. (1969): “The evaluation of economic forecasts”, in: *Economic Forecasts and Expectation*, ed. J. Mincer, 3–46. New York: Columbia University Press.
- Moneta, F. (2005): “Does the yield spread predict recessions in the euro area?”, *International Finance*, 8(2), 263-301.
- Oi, W. (1961): “The desirability of price instability under perfect competition”, *Econometrica*, 29(1), 58–64.
- Pindyck, R. S. (1991): “Irreversibility, Uncertainty and Investment”, *Journal of Economic Literature*, 29, 1110-1148.
- Romer, C (1990): “The great crash and the onset of the great depression”, *Quarterly Journal of Economics*, 105(3), 597–624.
- Rossi, B. / Sekhposyan, T. (2015): “Macroeconomic uncertainty indices based on nowcast and forecast error distributions”, *American Economic Review*, 105 (5), 650-655.
- Rudebusch, G. D. / Williams, J. C. (2009): “Forecasting recessions: The puzzle of the enduring power of the yield curve”, *Journal of Business & Economic Statistics*, 27(4), 492-503.

Schrimpf, A. / Sushko, V. (2019): “Beyond LIBOR: a primer on the new benchmark rates”, in: BIS Quarterly Review March.

Stokey, N. L. (2016): “Wait-and-see: Investment options under policy uncertainty”, *Review of Economic Dynamics*, 21, 246-265.

Summers, L. (2016): “Age of secular stagnation”, *Foreign Affairs*, 95(2), 2-9.

Wu, J. C. / Xia, F. D.(2016): “Measuring the macroeconomic impact of monetary policy at the zero lower bound”, *Journal of Money, Credit, and Banking*, 48(2-3), 253-291.

# Appendix

## Table A5: Univariate Benchmark Model - 12m Forecasting Horizon - Out-Of-Sample

Out-Of-Sample				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued No Signal Issued	A C	B D					L = 0.25	L = 0.75
Rates	3m EURIBOR			83%	78%	35%	1%	0.17	0.49
	3m EURIBOR (6m_diff)			43%	69%	4%	0%	0.24	0.72
	3m EURIBOR (12m_diff)			67%	68%	0%	0%	0.25	0.75
	10yr German Government Bond			57%	68%	0%	0%	0.25	0.75
	10yr German Government Bond (6m_diff)			49%	68%	0%	0%	0.25	0.75
	10yr German Government Bond (12m_diff)			55%	68%	0%	0%	0.25	0.75
Term Spread	Term Spread: 10y-3m			89%	74%	35%	8%	0.22	0.51
	Term Spread: 10y-3m (6m_diff)			51%	68%	2%	0%	0.25	0.74
	Term Spread: 10y-3m (12m_diff)			66%	68%	0%	0%	0.25	0.75
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate]			89%	75%	27%	2%	0.19	0.55
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (6m_diff)			51%	68%	0%	0%	0.25	0.75
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (12m_diff)			66%	68%	0%	0%	0.25	0.75
Money Supply	M1 (6m_ret)			77%	84%	55%	3%	0.13	0.35
	M1 (12m_ret)			95%	84%	87%	17%	0.16	0.14
	Real M1 (6m_ret)			78%	82%	51%	3%	0.14	0.37
	Real M1 (12m_ret)			93%	89%	78%	5%	0.09	0.18
	M2 (6m_ret)			83%	72%	20%	3%	0.23	0.61
	M2 (12m_ret)			91%	76%	35%	4%	0.20	0.50
	Real M2 (6m_ret)			81%	71%	18%	3%	0.23	0.62
	Real M2 (12m_ret)			89%	74%	31%	6%	0.22	0.53
	M3 (6m_ret)			76%	71%	15%	2%	0.23	0.65
Competitiveness	FX EUR/USD			89%	76%	38%	6%	0.20	0.48
	FX EUR/USD (6m_ret)			52%	68%	0%	0%	0.25	0.75
	FX EUR/USD (12m_ret)			52%	68%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate			87%	69%	18%	7%	0.26	0.63
	JPM Nominal Broad Effective FX Rate (6m_ret)			53%	68%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate (12m_ret)			51%	68%	0%	0%	0.25	0.75
	Terms of Trade			86%	74%	76%	28%	0.27	0.25
	Terms of Trade (6m_ret)			50%	68%	0%	0%	0.25	0.75
	Terms of Trade (12m_ret)			53%	68%	0%	0%	0.25	0.75
Sentiment	PMI			69%	74%	20%	1%	0.21	0.60
	PMI (6m_diff)			87%	78%	38%	3%	0.17	0.47
	PMI (12m_diff)			92%	82%	55%	4%	0.15	0.35
	Economic Sentiment			50%	68%	0%	0%	0.25	0.75
	Economic Sentiment (6m_diff)			91%	82%	51%	3%	0.14	0.37
	Economic Sentiment (12m_diff)			83%	75%	4%	4%	0.20	0.52
	Industrial Confidence			44%	68%	0%	0%	0.25	0.75
	Industrial Confidence (6m_diff)			92%	79%	47%	5%	0.17	0.41
	Industrial Confidence (12m_diff)			83%	71%	20%	4%	0.23	0.61
	Consumer Confidence			54%	68%	0%	0%	0.25	0.75
	Consumer Confidence (6m_diff)			80%	78%	44%	5%	0.18	0.44
	Consumer Confidence (12m_diff)			76%	74%	24%	3%	0.21	0.58
	Consumer Economic Situation			65%	76%	25%	0%	0.19	0.56
	Consumer Economic Situation (6m_diff)			82%	76%	40%	6%	0.20	0.47
	Consumer Economic Situation (12m_diff)			80%	79%	3%	3%	0.23	0.44
Refinancing	Business Climate			44%	68%	0%	0%	0.25	0.75
	Business Climate (6m_diff)			90%	80%	47%	4%	0.16	0.41
	Business Climate (12m_diff)			83%	71%	18%	4%	0.24	0.62
	Corporate Bonds: Investment Grade Spread			79%	77%	36%	3%	0.19	0.49
	Corporate Bonds: Investment Grade Spread (6m_diff)			87%	78%	35%	1%	0.17	0.49
	Corporate Bonds: Investment Grade Spread (12m_diff)			94%	84%	53%	2%	0.13	0.36
	High Yield Spread			70%	72%	16%	1%	0.22	0.63
	High Yield Spread (6m_diff)			86%	76%	31%	3%	0.19	0.52
	High Yield Spread (12m_diff)			95%	84%	55%	2%	0.13	0.35
	EZ Peripheral Bond Spread			76%	74%	53%	16%	0.24	0.39
Risk Aversion	EZ Peripheral Bond Spread (6m_diff)			81%	74%	29%	4%	0.21	0.54
	EZ Peripheral Bond Spread (12m_diff)			84%	82%	55%	4%	0.15	0.35
	MFI Loans to Private Sector (6m_ret)			66%	68%	0%	0%	0.25	0.75
	MFI Loans to Private Sector (12m_ret)			76%	66%	2%	3%	0.27	0.74
	Implied Rates Volatility			64%	75%	24%	1%	0.20	0.57
	Implied Rates Volatility (6m_diff)			87%	73%	36%	10%	0.23	0.50
	Implied Rates Volatility (12m_diff)			84%	73%	27%	5%	0.22	0.56
	VSTOXX			64%	68%	2%	1%	0.25	0.74
	VSTOXX (6m_ret)			71%	68%	7%	3%	0.26	0.70
	VSTOXX (12m_ret)			81%	68%	16%	7%	0.26	0.64
	VIX			75%	72%	16%	2%	0.22	0.63
	VIX (6m_ret)			76%	71%	20%	5%	0.24	0.61
Industrial Data	VIX (12m_ret)			92%	78%	44%	6%	0.19	0.44
	FX Basis EUR/USD			82%	76%	40%	6%	0.20	0.47
	FX Basis EUR/USD (6m_diff)			82%	70%	7%	0%	0.23	0.70
	FX Basis EUR/USD (12m_diff)			89%	76%	47%	10%	0.21	0.42
	Implied FX Vol			54%	71%	11%	0%	0.22	0.67
	Implied FX Vol (6m_ret)			72%	69%	20%	7%	0.25	0.62
	Implied FX Vol (12m_ret)			82%	71%	31%	10%	0.24	0.54
	LiborOIS			88%	82%	44%	0%	0.14	0.42
	Industrial Production: Industry excl. Constr. (6m_ret)			68%	71%	13%	2%	0.23	0.66
	Industrial Production: Industry excl. Constr. (12m_ret)			54%	69%	5%	0%	0.24	0.71
Inflation	Unemployment Rate			89%	78%	36%	3%	0.18	0.48
	Unemployment Rate (6m_ret)			47%	68%	0%	0%	0.25	0.75
	Unemployment Rate (12m_ret)			66%	68%	0%	0%	0.25	0.75
	Manufact. New Orders (6m_ret)			72%	72%	16%	1%	0.22	0.63
	Manufact. New Orders (12m_ret)			60%	69%	9%	3%	0.25	0.69
	Industr. Turnover: Manufacturing (6m_ret)			64%	70%	11%	2%	0.24	0.67
	Industr. Turnover: Manufacturing (12m_ret)			53%	68%	0%	0%	0.25	0.75
	MFG Stocks of Finished Products			54%	70%	7%	0%	0.23	0.70
	MFG Stocks of Finished Products (6m_diff)			93%	77%	47%	9%	0.20	0.42
	MFG Stocks of Finished Products (12m_diff)			87%	78%	42%	4%	0.18	0.45
	Retail Sales (6m_ret)			76%	73%	22%	3%	0.22	0.59
	Retail Sales (12m_ret)			67%	67%	7%	4%	0.26	0.71
	New Passenger Cars (6m_ret)			63%	68%	0%	0%	0.25	0.75
	New Passenger Cars (12m_ret)			69%	72%	18%	3%	0.22	0.62
	HICP (6m_ret)			64%	68%	0%	0%	0.25	0.75
HICP (12m_ret)			61%	69%	5%	0%	0.24	0.71	
HICP excl. Energy, Food, Alcohol & Tobacco (6m_ret)			64%	68%	0%	0%	0.25	0.75	
HICP excl. Energy, Food, Alcohol & Tobacco (12m_ret)			68%	68%	0%	0%	0.25	0.75	
Domestic PPI: Industry excluding Construction (6m_ret)			61%	68%	0%	0%	0.25	0.75	
Domestic PPI: Industry excluding Construction (12m_ret)			66%	68%	2%	0%	0.25	0.74	
Commodities	Crude Oil			81%	78%	71%	18%	0.21	0.26
	Crude Oil (6m_diff)			47%	68%	0%	0%	0.25	0.75
	Crude Oil (12m_diff)			53%	68%	0%	0%	0.25	0.75
	Gold			81%	56%	53%	42%	0.43	0.46
	Gold (6m_diff)			49%	68%	0%	0%	0.25	0.75
Wealth	Gold (12m_diff)			57%	68%	0%	0%	0.25	0.75
	ESTOXX50 (6m_ret)			77%	69%	16%	5%	0.25	0.64
	ESTOXX50 (12m_ret)			69%	70%	9%	1%	0.23	0.68
	Residential Building Permits (6m_ret)			93%	75%	35%	5%	0.20	0.50
	Residential Building Permits (12m_ret)			88%	74%	31%	5%	0.21	0.53

**Table A6: Submodel 1 - Monetary Transmission Channels - Out-Of-Sample**

Out-Of-Sample				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive rate vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued No Signal Issued	A C	B D					L = 0.25	L = 0.75
<b>Channel: Money Supply</b>									
Real M1 (12m_ret)				94%	89%	80%	6%	0.10	0.17
				93%	89%	78%	5%	0.09	0.18
<b>Channel: Competitiveness</b>									
FX EUR/USD				91%	80%	80%	20%	0.20	0.20
Terms of Trade				89%	76%	38%	6%	0.20	0.48
				86%	74%	76%	28%	0.27	0.25
<b>Channel: Sentiment</b>									
PMI (12m_diff)				85%	78%	40%	4%	0.18	0.46
Economic Sentiment (6m_diff)				92%	82%	55%	4%	0.15	0.35
Industrial Confidence (6m_diff)				91%	82%	51%	3%	0.14	0.37
Business Climate (6m_diff)				92%	79%	47%	5%	0.17	0.41
Consumer Economic Situation (12m_diff)				90%	80%	47%	4%	0.16	0.41
Consumer Confidence (6m_diff)				80%	79%	42%	3%	0.17	0.44
				80%	78%	44%	5%	0.18	0.44
<b>Channel: Refinancing</b>									
Corporate Bonds: Investment Grade Spread				88%	84%	56%	3%	0.14	0.34
EZ Peripheral Bond Spread (12m_diff)				79%	77%	36%	3%	0.19	0.49
High Yield Spread (12m_diff)				84%	82%	55%	4%	0.15	0.35
				95%	84%	55%	2%	0.13	0.35
<b>Channel: Preference for Risk</b>									
LiborOIS				80%	76%	31%	2%	0.19	0.52
Implied Rates Volatility				88%	82%	44%	0%	0.14	0.42
FX Basis EUR/USD				64%	75%	24%	1%	0.20	0.57
				82%	76%	40%	6%	0.20	0.47
<b>Channel: Industrial Data</b>									
Retail Sales (6m_ret)				86%	85%	62%	3%	0.12	0.36
MFG Stocks of Finished Products (6m_diff)				76%	76%	22%	3%	0.22	0.59
New Passenger Cars (12m_ret)				93%	77%	47%	9%	0.20	0.42
				69%	72%	18%	3%	0.22	0.62
<b>Channel: Inflation</b>									
HICP (12m_ret)				68%	71%	11%	0%	0.22	0.67
Domestic PPI: Industry excluding Construction (12m_ret)				61%	69%	5%	0%	0.24	0.71
				66%	68%	2%	0%	0.25	0.74
<b>Channel: Commodities</b>									
Crude Oil				84%	79%	76%	19%	0.20	0.23
Gold				81%	78%	71%	18%	0.21	0.26
				81%	56%	53%	42%	0.43	0.46

**Table A7: Submodel 2 - Bivariate Specification - Out-Of-Sample**

Out-Of-Sample				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive rate vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued No Signal Issued	A C	B D					L = 0.25	L = 0.75
Real M1 (12m_ret) & PMI (12m_diff)				99%	92%	78%	2%	0.07	0.17
Real M1 (12m_ret) & Investment Grade Spreads				97%	92%	87%	6%	0.08	0.11
Real M1 (12m_ret) & Terms of Trade				96%	84%	93%	20%	0.17	0.10
Real M1 (12m_ret) & Retail Sales (6m_ret)				97%	92%	89%	7%	0.08	0.10
Real M1 (12m_ret) & Crude Oil				96%	85%	91%	17%	0.15	0.11
PMI (12m_diff) & Investment Grade Spreads				93%	85%	56%	2%	0.13	0.33
PMI (12m_diff) & Terms of Trade				100%	82%	96%	24%	0.19	0.09
PMI (12m_diff) & Retail Sales (6m_ret)				93%	83%	53%	3%	0.14	0.36
PMI (12m_diff) & Crude Oil				99%	86%	95%	17%	0.14	0.08
Corporate Investment Grade Spreads & Terms of Trade				89%	80%	82%	21%	0.21	0.19
Corporate Investment Grade Spreads & Retail Sales (6m_ret)				79%	80%	36%	2%	0.17	0.48
Corporate Investment Grade Spreads & Crude Oil				93%	81%	89%	22%	0.19	0.14
Terms of Trade & Retail Sales (6m_ret)				90%	81%	82%	19%	0.19	0.18
Terms of Trade & Crude Oil				86%	77%	76%	23%	0.23	0.23
Retail Sales (6m_ret) & Crude Oil				87%	80%	75%	18%	0.20	0.24
Channels: Money Supply & Industrial				97%	94%	91%	4%	0.05	0.08
Channels: Money Supply & Refinancing				98%	92%	80%	2%	0.07	0.16
Channels: Money Supply & Competitiveness				97%	87%	91%	15%	0.14	0.11
Channels: Money Supply & Sentiment				97%	92%	80%	2%	0.07	0.16
Channels: Money Supply & Commodities				96%	88%	89%	13%	0.12	0.11
Channels: Industrial & Refinancing				88%	88%	67%	2%	0.10	0.25
Channels: Industrial & Competitiveness				87%	87%	67%	4%	0.11	0.26
Channels: Industrial & Sentiment				86%	87%	64%	2%	0.11	0.28
Channels: Industrial & Commodities				99%	90%	91%	11%	0.11	0.10
Channels: Refinancing & Competitiveness				88%	84%	55%	3%	0.14	0.35
Channels: Refinancing & Sentiment				86%	85%	55%	2%	0.13	0.34
Channels: Refinancing & Commodities				98%	91%	82%	6%	0.09	0.15
Channels: Competitiveness & Sentiment				84%	86%	55%	0%	0.11	0.34
Channels: Competitiveness & Commodities				95%	77%	84%	25%	0.23	0.19
Channels: Sentiment & Commodities				99%	91%	85%	7%	0.09	0.13

**Table A8: Submodel 3 - Unstable Surges - Out-Of-Sample**

Out-Of-Sample				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive rate vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued No Signal Issued	A C	B D					L = 0.25	L = 0.75
<b>Money Supply</b>									
Real M1 & HP_Diff Lag (t0)				97%	89%	89%	1%	0.11	0.11
Real M1 & HP_Diff Lag (t-1yr)				97%	92%	87%	6%	0.07	0.11
Real M1 & HP_Diff Lag (t-2yr)				94%	90%	75%	4%	0.09	0.20
Single Indicator: Real M1 (12m_ret)				93%	89%	78%	5%	0.09	0.18
<b>Equity Markets</b>									
ESTOXX50 (12m_ret) & HP_Diff Lag (t0)				67%	72%	13%	2%	0.23	0.66
ESTOXX50 (12m_ret) & HP_Diff Lag (t-1yr)				73%	72%	15%	3%	0.24	0.65
ESTOXX50 (12m_ret) & HP_Diff Lag (t-2yr)				72%	73%	16%	2%	0.23	0.63
Single Indicator: ESTOXX50 (12m_ret)				69%	70%	9%	1%	0.23	0.68
<b>Building Permits</b>									
Residential Building Permits (6m_ret) & HP_Diff Lag (t0)				96%	77%	38%	6%	0.20	0.48
Residential Building Permits (6m_ret) & HP_Diff Lag (t-1yr)				95%	81%	47%	4%	0.16	0.41
Residential Building Permits (6m_ret) & HP_Diff Lag (t-2yr)				92%	78%	36%	4%	0.19	0.49
Single Indicator: Residential Building Permits (6m_ret)				93%	75%	35%	5%	0.20	0.50
<b>Sentiment</b>									
PMI (12m_diff) & HP_Diff Lag (t0)				100%	86%	56%	1%	0.12	0.33
PMI (12m_diff) & HP_Diff Lag (t-1yr)				92%	83%	53%	4%	0.15	0.36
PMI (12m_diff) & HP_Diff Lag (t-2yr)				92%	83%	55%	4%	0.14	0.35
Single Indicator: PMI (12m_diff)				92%	82%	55%	4%	0.15	0.35
<b>Inflation</b>									
HICP (12m_ret) & HP_Diff Lag (t0)				64%	51%	20%	4%	0.47	0.69
HICP (12m_ret) & HP_Diff Lag (t-1yr)				74%	83%	49%	2%	0.15	0.39
HICP (12m_ret) & HP_Diff Lag (t-2yr)				71%	79%	33%	1%	0.17	0.51
Single Indicator: HICP (12m_ret)				61%	69%	5%	0%	0.24	0.71
<b>Retail</b>									
Retail Sales (6m_ret) & HP_Diff Lag (t0)				84%	85%	71%	10%	0.14	0.24
Retail Sales (6m_ret) & HP_Diff Lag (t-1yr)				78%	78%	36%	3%	0.18	0.49
Retail Sales (6m_ret) & HP_Diff Lag (t-2yr)				76%	75%	24%	3%	0.21	0.58
Single Indicator: Retail Sales (6m_ret)				76%	73%	22%	3%	0.22	0.59
<b>Credit Dynamics</b>									
MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t0)				80%	75%	24%	3%	0.21	0.52
MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-1yr)				93%	76%	33%	6%	0.21	0.75
MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-2yr)				82%	78%	29%	1%	0.18	0.53
Single Indicator: MFI Loans to Private Sector (12m_ret)				76%	66%	2%	3%	0.27	0.74
<b>Oil</b>									
Crude Oil & HP_Diff Lag (t0)				89%	76%	78%	25%	0.25	0.23
Crude Oil & HP_Diff Lag (t-1yr)				89%	78%	73%	19%	0.21	0.25
Crude Oil & HP_Diff Lag (t-2yr)				91%	80%	78%	20%	0.20	0.21
Single Indicator: Crude Oil				81%	78%	71%	18%	0.21	0.26
<b>Central Bank Policy</b>									
3m EURIBOR (12m_diff) & HP_Diff Lag (t0)				74%	70%	3%	0%	0.25	0.75
3m EURIBOR (12m_diff) & HP_Diff Lag (t-1yr)				91%	87%	65%	4%	0.12	0.27
3m EURIBOR (12m_diff) & HP_Diff Lag (t-2yr)				66%	70%	0%	0%	0.25	0.75
Single Indicator: 3m EURIBOR				83%	78%	35%	1%	0.17	0.49

**Table A9: The Univariate Benchmark Model over the 6m Forecasting Horizon**

6m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Averse	
Transmission Channel	Classification	Recession		True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued	A	B					L = 0.25	L = 0.75
	No Signal Issued	C	D						
Rates	3m EURIBOR			62%	77%	0%	0%	0.25	0.75
	3m EURIBOR (6m_diff)			58%	80%	14%	1%	0.22	0.65
	3m EURIBOR (12m_diff)			47%	77%	0%	0%	0.25	0.75
	10yr German Government Bond			50%	77%	0%	0%	0.25	0.75
	10yr German Government Bond (6m_diff)			64%	79%	7%	0%	0.23	0.70
	10yr German Government Bond (12m_diff)			62%	77%	0%	0%	0.25	0.75
Term Spread	Term Spread: 10y-3m			70%	83%	1%	1%	0.18	0.51
	Term Spread: 10y-3m (6m_diff)			52%	77%	0%	0%	0.25	0.75
	Term Spread: 10y-3m (12m_diff)			60%	77%	0%	0%	0.25	0.75
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate]			85%	79%	37%	9%	0.22	0.49
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (6m_diff)			58%	77%	0%	0%	0.25	0.75
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (12m_diff)			69%	77%	0%	0%	0.25	0.75
Money Supply	M1 (6m_ret)			80%	84%	44%	4%	0.17	0.43
	M1 (12m_ret)			93%	90%	70%	3%	0.10	0.24
	Real M1 (6m_ret)			80%	84%	44%	4%	0.17	0.43
	Real M1 (12m_ret)			94%	91%	70%	2%	0.09	0.23
	M2 (6m_ret)			51%	77%	0%	0%	0.25	0.75
	M2 (12m_ret)			52%	77%	0%	0%	0.25	0.75
	Real M2 (6m_ret)			52%	77%	0%	0%	0.25	0.75
	Real M2 (12m_ret)			49%	77%	0%	0%	0.25	0.75
	M3 (6m_ret)			49%	77%	0%	0%	0.25	0.75
	M3 (12m_ret)			52%	77%	0%	0%	0.25	0.75
	Real M3 (6m_ret)			53%	77%	0%	0%	0.25	0.75
	Real M3 (12m_ret)			50%	77%	0%	0%	0.25	0.75
Competitiveness	FX EUR/USD			81%	81%	40%	6%	0.20	0.47
	FX EUR/USD (6m_ret)			55%	77%	0%	0%	0.25	0.75
	FX EUR/USD (12m_ret)			54%	77%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate			66%	75%	0%	2%	0.27	0.76
	JPM Nominal Broad Effective FX Rate (6m_ret)			54%	77%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate (12m_ret)			56%	77%	0%	0%	0.25	0.75
	Terms of Trade			88%	83%	63%	10%	0.17	0.31
	Terms of Trade (6m_ret)			61%	77%	0%	0%	0.25	0.75
	Terms of Trade (12m_ret)			69%	77%	0%	0%	0.25	0.75
	PMI			86%	85%	56%	6%	0.16	0.35
Sentiment	PMI (6m_diff)			84%	86%	47%	3%	0.15	0.41
	PMI (12m_diff)			95%	90%	74%	5%	0.10	0.20
	Economic Sentiment			75%	81%	28%	3%	0.20	0.55
	Economic Sentiment (6m_diff)			94%	90%	70%	3%	0.10	0.24
	Economic Sentiment (12m_diff)			90%	88%	60%	4%	0.13	0.31
	Industrial Confidence			64%	79%	16%	2%	0.22	0.63
	Industrial Confidence (6m_diff)			92%	89%	65%	4%	0.12	0.27
	Industrial Confidence (12m_diff)			88%	85%	51%	5%	0.16	0.38
	Consumer Confidence			83%	83%	42%	5%	0.18	0.45
	Consumer Confidence (6m_diff)			89%	88%	63%	5%	0.13	0.29
	Consumer Confidence (12m_diff)			88%	82%	51%	8%	0.18	0.39
	Consumer Economic Situation			91%	90%	70%	4%	0.11	0.24
	Consumer Economic Situation (6m_diff)			86%	86%	53%	5%	0.15	0.36
	Consumer Economic Situation (12m_diff)			89%	87%	65%	6%	0.13	0.28
	Business Climate			65%	78%	14%	3%	0.24	0.65
	Business Climate (6m_diff)			93%	89%	65%	4%	0.12	0.27
	Business Climate (12m_diff)			89%	84%	47%	5%	0.17	0.41
	Refinancing	Corporate Bonds: Investment Grade Spread			91%	85%	51%	5%	0.16
Corporate Bonds: Investment Grade Spread (6m_diff)				61%	82%	23%	0%	0.19	0.58
Corporate Bonds: Investment Grade Spread (12m_diff)				77%	85%	35%	0%	0.16	0.49
High Yield Spread				87%	79%	33%	7%	0.22	0.52
High Yield Spread (6m_diff)				67%	82%	28%	1%	0.19	0.54
High Yield Spread (12m_diff)				80%	90%	58%	1%	0.11	0.32
EZ Peripheral Bond Spread				77%	87%	47%	1%	0.14	0.40
EZ Peripheral Bond Spread (6m_diff)				74%	80%	12%	0%	0.22	0.66
EZ Peripheral Bond Spread (12m_diff)				83%	82%	30%	3%	0.20	0.53
MFI Loans to Private Sector (6m_ret)				54%	77%	0%	0%	0.25	0.75
MFI Loans to Private Sector (12m_ret)			54%	77%	0%	0%	0.25	0.75	
Risk Aversion	Implied Rates Volatility			83%	81%	35%	6%	0.20	0.50
	Implied Rates Volatility (6m_diff)			63%	80%	12%	0%	0.22	0.66
	Implied Rates Volatility (12m_diff)			72%	81%	23%	1%	0.20	0.58
	VSTOXX			71%	75%	12%	6%	0.26	0.68
	VSTOXX (6m_ret)			57%	77%	2%	1%	0.25	0.73
	VSTOXX (12m_ret)			66%	78%	9%	2%	0.24	0.69
	VIX			77%	79%	23%	5%	0.23	0.59
	VIX (6m_ret)			58%	79%	9%	1%	0.23	0.68
	VIX (12m_ret)			70%	81%	26%	2%	0.20	0.56
	FX Basis EUR/USD			80%	82%	40%	6%	0.19	0.47
	FX Basis EUR/USD (6m_diff)			55%	77%	0%	0%	0.25	0.75
	FX Basis EUR/USD (12m_diff)			70%	79%	9%	0%	0.23	0.68
Industrial Data	Implied FX Vol			71%	81%	23%	1%	0.20	0.58
	Implied FX Vol (6m_ret)			60%	78%	9%	2%	0.24	0.69
	Implied FX Vol (12m_ret)			68%	78%	14%	3%	0.24	0.65
	LiborOIS			90%	87%	51%	2%	0.14	0.37
	Industrial Production: Industry excl. Constr. (6m_ret)			79%	80%	21%	2%	0.21	0.60
	Industrial Production: Industry excl. Constr. (12m_ret)			67%	77%	12%	3%	0.25	0.67
	Unemployment Rate			54%	77%	0%	0%	0.25	0.75
	Unemployment Rate (6m_ret)			79%	79%	16%	3%	0.23	0.63
	Unemployment Rate (12m_ret)			67%	74%	5%	5%	0.27	0.73
	Manufact. New Orders (6m_ret)			80%	84%	35%	1%	0.17	0.49
	Manufact. New Orders (12m_ret)			70%	78%	14%	3%	0.24	0.65
	Industr. Turnover: Manufacturing (6m_ret)			66%	79%	14%	1%	0.23	0.65
	Industr. Turnover: Manufacturing (12m_ret)			52%	77%	0%	0%	0.25	0.75
	MFG Stocks of Finished Products			63%	80%	14%	0%	0.22	0.65
	MFG Stocks of Finished Products (6m_diff)			85%	86%	47%	3%	0.15	0.41
	MFG Stocks of Finished Products (12m_diff)			89%	86%	53%	5%	0.15	0.36
	Retail Sales (6m_ret)			90%	86%	51%	4%	0.15	0.38
	Retail Sales (12m_ret)			87%	82%	47%	8%	0.19	0.42
New Passenger Cars (6m_ret)			75%	78%	12%	3%	0.24	0.67	
New Passenger Cars (12m_ret)			80%	81%	33%	5%	0.21	0.52	
Inflation	HICP (6m_ret)			72%	79%	7%	0%	0.23	0.70
	HICP (12m_ret)			86%	86%	37%	0%	0.16	0.47
	HICP excl. Energy, Food, Alcohol & Tobacco (6m_ret)			69%	74%	0%	4%	0.28	0.76
	HICP excl. Energy, Food, Alcohol & Tobacco (12m_ret)			70%	72%	0%	6%	0.30	0.77
	Domestic PPI: Industry excluding Construction (6m_ret)			68%	77%	0%	0%	0.25	0.75
	Domestic PPI: Industry excluding Construction (12m_ret)			78%	81%	28%	3%	0.20	0.55
Commodities	Crude Oil			82%	80%	37%	8%	0.21	0.49
	Crude Oil (6m_diff)			53%	77%	0%	0%	0.25	0.75
	Crude Oil (12m_diff)			51%	77%	0%	0%	0.25	0.75
	Gold			76%	88%	51%	1%	0.13	0.37
	Gold (6m_diff)			56%	77%	0%	0%	0.25	0.75
	Gold (12m_diff)			60%	77%	0%	0%	0.25	0.75
Wealth	ESTOXX50 (6m_ret)			74%	79%	23%	5%	0.23	0.59
	ESTOXX50 (12m_ret)			77%	78%	21%	6%	0.24	0.61
	Residential Building Permits (6m_ret)			78%	84%	40%	3%	0.17	0.46
	Residential Building Permits (12m_ret)			81%	82%	40%	5%	0.19	0.47

**Table A10: The Univariate Benchmark Model over the 18m Forecasting Horizon**

18m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse		
Transmission Channel	Classification	Recession		No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)		
	Signal Issued No Signal Issued	A C	B D	L = 0.25					L = 0.75		
Rates	3m EURIBOR				65%	69%	39%	13%	0.25	0.49	
	3m EURIBOR (6m_diff)				38%	62%	0%	0%	0.25	0.75	
	3m EURIBOR (12m_diff)				68%	68%	22%	4%	0.22	0.59	
	10yr German Government Bond				52%	62%	0%	0%	0.25	0.75	
	10yr German Government Bond (6m_diff)				54%	63%	3%	0%	0.24	0.73	
	10yr German Government Bond (12m_diff)				51%	62%	0%	0%	0.25	0.75	
Term Spread	Term Spread: 10y-3m				70%	70%	46%	15%	0.25	0.44	
	Term Spread: 10y-3m (6m_diff)				56%	62%	0%	0%	0.25	0.75	
	Term Spread: 10y-3m (12m_diff)				71%	66%	25%	9%	0.26	0.58	
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate]				84%	76%	61%	15%	0.21	0.33	
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (6m_diff)				66%	69%	18%	0%	0.21	0.62	
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (12m_diff)				79%	76%	67%	19%	0.22	0.29	
Money Supply	M1 (6m_ret)				84%	79%	66%	13%	0.18	0.29	
	M1 (12m_ret)				89%	79%	73%	17%	0.19	0.24	
	Real M1 (6m_ret)				84%	78%	67%	15%	0.19	0.28	
	Real M1 (12m_ret)				80%	81%	75%	15%	0.17	0.23	
	M2 (6m_ret)				52%	62%	0%	0%	0.25	0.75	
	M2 (12m_ret)				52%	62%	0%	0%	0.25	0.75	
	Real M2 (6m_ret)				50%	62%	0%	0%	0.25	0.75	
	Real M2 (12m_ret)				49%	62%	0%	0%	0.25	0.75	
	M3 (6m_ret)				50%	62%	0%	0%	0.25	0.75	
	M3 (12m_ret)				49%	62%	0%	0%	0.25	0.75	
	Real M3 (6m_ret)				52%	62%	0%	0%	0.25	0.75	
	Real M3 (12m_ret)				51%	62%	0%	0%	0.25	0.75	
Competitiveness	FX EUR/USD				82%	70%	54%	20%	0.27	0.40	
	FX EUR/USD (6m_ret)				54%	64%	6%	0%	0.24	0.71	
	FX EUR/USD (12m_ret)				54%	62%	0%	0%	0.25	0.75	
	JPM Nominal Broad Effective FX Rate				64%	63%	24%	12%	0.28	0.60	
	JPM Nominal Broad Effective FX Rate (6m_ret)				61%	59%	10%	10%	0.30	0.70	
	JPM Nominal Broad Effective FX Rate (12m_ret)				64%	63%	28%	16%	0.30	0.58	
	Terms of Trade				82%	74%	66%	20%	0.24	0.31	
	Terms of Trade (6m_ret)				64%	64%	12%	4%	0.25	0.67	
	Terms of Trade (12m_ret)				72%	65%	12%	25%	0.31	0.44	
	PMI				57%	71%	30%	4%	0.20	0.54	
	PMI (6m_diff)				76%	73%	51%	14%	0.23	0.40	
	PMI (12m_diff)				78%	74%	51%	12%	0.21	0.40	
Sentiment	Economic Sentiment				48%	62%	0%	0%	0.25	0.75	
	Economic Sentiment (6m_diff)				73%	75%	51%	9%	0.19	0.39	
	Economic Sentiment (12m_diff)				64%	72%	36%	6%	0.20	0.50	
	Industrial Confidence				60%	62%	0%	0%	0.25	0.75	
	Industrial Confidence (6m_diff)				70%	74%	45%	7%	0.19	0.43	
	Industrial Confidence (12m_diff)				61%	64%	12%	4%	0.25	0.67	
	Consumer Confidence				62%	69%	28%	6%	0.23	0.55	
	Consumer Confidence (6m_diff)				71%	71%	45%	12%	0.23	0.44	
	Consumer Confidence (12m_diff)				62%	70%	42%	12%	0.24	0.47	
	Consumer Economic Situation				67%	72%	49%	14%	0.23	0.42	
	Consumer Economic Situation (6m_diff)				73%	70%	48%	17%	0.26	0.43	
	Consumer Economic Situation (12m_diff)				69%	70%	45%	14%	0.24	0.45	
	Business Climate				60%	62%	0%	0%	0.25	0.75	
	Business Climate (6m_diff)				71%	74%	45%	8%	0.20	0.44	
	Business Climate (12m_diff)				63%	62%	3%	3%	0.24	0.68	
	Refinancing	Corporate Bonds: Investment Grade Spread				82%	83%	69%	8%	0.14	0.26
		Corporate Bonds: Investment Grade Spread (6m_diff)				64%	72%	30%	2%	0.19	0.53
		Corporate Bonds: Investment Grade Spread (12m_diff)				72%	77%	43%	3%	0.16	0.43
High Yield Spread					69%	66%	33%	13%	0.27	0.54	
High Yield Spread (6m_diff)					64%	71%	33%	5%	0.20	0.52	
High Yield Spread (12m_diff)					68%	76%	45%	5%	0.17	0.43	
EZ Peripheral Bond Spread					73%	73%	45%	10%	0.21	0.44	
EZ Peripheral Bond Spread (6m_diff)					80%	78%	45%	1%	0.15	0.42	
EZ Peripheral Bond Spread (12m_diff)					64%	68%	15%	10%	0.29	0.66	
MFI Loans to Private Sector (6m_ret)					54%	62%	0%	0%	0.25	0.75	
MFI Loans to Private Sector (12m_ret)					60%	68%	30%	8%	0.24	0.55	
Risk Aversion		Implied Rates Volatility				74%	74%	51%	11%	0.21	0.40
	Implied Rates Volatility (6m_diff)				63%	69%	33%	8%	0.23	0.52	
	Implied Rates Volatility (12m_diff)				62%	66%	22%	6%	0.24	0.60	
	VSTOXX				63%	62%	12%	7%	0.28	0.68	
	VSTOXX (6m_ret)				57%	61%	7%	6%	0.27	0.71	
	VSTOXX (12m_ret)				64%	61%	15%	10%	0.29	0.66	
	VIX				69%	64%	28%	14%	0.28	0.57	
	VIX (6m_ret)				59%	65%	24%	9%	0.26	0.59	
	VIX (12m_ret)				68%	69%	37%	11%	0.24	0.50	
	FX Basis EUR/USD				77%	71%	55%	19%	0.25	0.38	
	FX Basis EUR/USD (6m_diff)				57%	65%	9%	0%	0.23	0.68	
	FX Basis EUR/USD (12m_diff)				70%	74%	37%	4%	0.18	0.48	
	Implied FX Vol				62%	70%	30%	5%	0.21	0.54	
	Implied FX Vol (6m_ret)				56%	65%	15%	4%	0.24	0.65	
	Implied FX Vol (12m_ret)				59%	65%	16%	6%	0.25	0.64	
	LiborOIS				75%	79%	55%	6%	0.16	0.35	
	Industrial Data	Industrial Production: Industry excl. Constr. (6m_ret)				53%	65%	10%	2%	0.24	0.68
		Industrial Production: Industry excl. Constr. (12m_ret)				60%	62%	0%	0%	0.25	0.75
Unemployment Rate					61%	74%	31%	0%	0.17	0.51	
Unemployment Rate (6m_ret)					58%	64%	10%	3%	0.24	0.68	
Unemployment Rate (12m_ret)					51%	62%	0%	0%	0.25	0.75	
Manufact. New Orders (6m_ret)					53%	65%	10%	1%	0.23	0.67	
Manufact. New Orders (12m_ret)					57%	62%	0%	0%	0.25	0.75	
Industr. Turnover: Manufacturing (6m_ret)					43%	62%	0%	0%	0.25	0.75	
Industr. Turnover: Manufacturing (12m_ret)					70%	68%	19%	2%	0.22	0.61	
MFG Stocks of Finished Products					64%	66%	10%	0%	0.22	0.67	
MFG Stocks of Finished Products (6m_diff)					69%	71%	43%	11%	0.23	0.45	
MFG Stocks of Finished Products (12m_diff)					63%	69%	22%	3%	0.21	0.59	
Retail Sales (6m_ret)					75%	71%	48%	14%	0.23	0.43	
Retail Sales (12m_ret)					70%	71%	45%	13%	0.24	0.45	
New Passenger Cars (6m_ret)					73%	71%	42%	11%	0.23	0.46	
New Passenger Cars (12m_ret)					80%	75%	54%	12%	0.21	0.38	
Inflation		HICP (6m_ret)				70%	71%	37%	7%	0.21	0.49
		HICP (12m_ret)				75%	67%	52%	23%	0.29	0.42
	HICP excl. Energy, Food, Alcohol & Tobacco (6m_ret)				66%	59%	15%	14%	0.32	0.67	
	HICP excl. Energy, Food, Alcohol & Tobacco (12m_ret)				63%	54%	0%	12%	0.34	0.78	
	Domestic PPI: Industry excluding Construction (6m_ret)				74%	66%	31%	12%	0.26	0.55	
	Domestic PPI: Industry excluding Construction (12m_ret)				81%	70%	57%	22%	0.27	0.38	
Commodities	Crude Oil				79%	74%	61%	19%	0.24	0.34	
	Crude Oil (6m_diff)				53%	62%	0%	0%	0.25	0.75	
	Crude Oil (12m_diff)				50%	62%	0%	0%	0.25	0.75	
	Gold				76%	65%	49%	25%	0.31	0.44	
	Gold (6m_diff)				58%	62%	7%	4%	0.26	0.70	
	Gold (12m_diff)				67%	65%	28%	12%	0.27	0.57	
Wealth	ESTOXX50 (6m_ret)				64%	66%	27%	10%	0.26	0.57	
	ESTOXX50 (12m_ret)				65%	60%	24%	18%	0.32	0.61	
	Residential Building Permits (6m_ret)				69%	67%	40%	16%	0.27	0.49	
	Residential Building Permits (12m_ret)				68%	65%	30%	13%	0.27	0.56	

**Table A11: The Univariate Benchmark Model over the 24m Forecasting Horizon**

24m Forecasting Horizon			AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse	
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C )	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued	A	B						L = 0.25
	No Signal Issued	C	D						
Rates	3m EURIBOR			63%	59%	42%	27%	0.35	0.50
	3m EURIBOR (6m_diff)			64%	53%	0%	0%	0.25	0.75
	3m EURIBOR (12m_diff)			68%	75%	59%	12%	0.19	0.33
	10Yr German Government Bond			51%	48%	19%	27%	0.40	0.67
	10Yr German Government Bond (6m_diff)			50%	56%	5%	0%	0.24	0.71
	10Yr German Government Bond (12m_diff)			57%	56%	37%	28%	0.37	0.54
Term Spread	Term Spread: 10y-3m			67%	64%	53%	26%	0.31	0.42
	Term Spread: 10y-3m (6m_diff)			55%	60%	15%	0%	0.21	0.64
	Term Spread: 10y-3m (12m_diff)			64%	63%	56%	30%	0.34	0.41
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate]			80%	75%	70%	21%	0.23	0.28
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (6m_diff)			64%	62%	43%	22%	0.31	0.48
	Term Spread: 10y-Switch[3m Euribor/Shadow Rate] (12m_diff)			73%	71%	71%	29%	0.29	0.29
Money Supply	M1 (6m_ret)			79%	70%	67%	27%	0.28	0.31
	M1 (12m_ret)			80%	74%	77%	29%	0.27	0.24
	Real M1 (6m_ret)			79%	70%	67%	28%	0.29	0.32
	Real M1 (12m_ret)			81%	73%	77%	30%	0.28	0.25
	M2 (6m_ret)			50%	53%	0%	0%	0.25	0.75
	M2 (12m_ret)			50%	53%	0%	0%	0.25	0.75
	Real M2 (6m_ret)			53%	53%	0%	0%	0.25	0.75
	Real M2 (12m_ret)			48%	53%	0%	0%	0.25	0.75
	M3 (6m_ret)			52%	59%	16%	3%	0.23	0.63
	M3 (12m_ret)			51%	63%	25%	3%	0.21	0.57
Competitiveness	Real M3 (6m_ret)			53%	60%	29%	13%	0.28	0.56
	Real M3 (12m_ret)			52%	62%	29%	9%	0.24	0.55
	FX EUR/USD			84%	72%	70%	27%	0.28	0.29
	FX EUR/USD (6m_ret)			51%	54%	13%	10%	0.29	0.68
	FX EUR/USD (12m_ret)			51%	53%	0%	0%	0.25	0.75
	JPM Nominal Broad Effective FX Rate			69%	63%	57%	32%	0.35	0.40
	JPM Nominal Broad Effective FX Rate (6m_ret)			57%	53%	32%	29%	0.39	0.58
	JPM Nominal Broad Effective FX Rate (12m_ret)			62%	54%	41%	33%	0.40	0.53
	Terms of Trade			79%	70%	68%	28%	0.29	0.31
	Terms of Trade (6m_ret)			66%	61%	54%	33%	0.36	0.43
Terms of Trade (12m_ret)			71%	68%	65%	29%	0.31	0.34	
Sentiment	PMI			48%	62%	30%	10%	0.25	0.55
	PMI (6m_diff)			68%	64%	56%	28%	0.32	0.40
	PMI (12m_diff)			66%	66%	52%	22%	0.29	0.42
	Economic Sentiment			45%	53%	0%	0%	0.25	0.75
	Economic Sentiment (6m_diff)			62%	64%	49%	23%	0.30	0.44
	Economic Sentiment (12m_diff)			53%	65%	35%	9%	0.23	0.51
	Industrial Confidence			60%	73%	43%	1%	0.15	0.43
	Industrial Confidence (6m_diff)			59%	68%	46%	12%	0.23	0.44
	Industrial Confidence (12m_diff)			51%	56%	6%	0%	0.23	0.70
	Consumer Confidence			59%	63%	48%	23%	0.30	0.45
	Consumer Confidence (6m_diff)			63%	61%	41%	21%	0.31	0.50
	Consumer Confidence (12m_diff)			53%	62%	43%	22%	0.31	0.48
	Consumer Economic Situation			61%	64%	48%	22%	0.30	0.44
	Consumer Economic Situation (6m_diff)			66%	62%	47%	26%	0.32	0.46
	Consumer Economic Situation (12m_diff)			60%	61%	43%	23%	0.32	0.49
Refinancing	Business Climate			61%	72%	41%	1%	0.16	0.45
	Business Climate (6m_diff)			59%	67%	46%	14%	0.24	0.44
	Business Climate (12m_diff)			53%	57%	8%	0%	0.23	0.69
	Corporate Bonds: Investment Grade Spread			79%	82%	73%	10%	0.14	0.22
	Corporate Bonds: Investment Grade Spread (6m_diff)			60%	65%	41%	13%	0.25	0.48
	Corporate Bonds: Investment Grade Spread (12m_diff)			66%	68%	42%	9%	0.21	0.46
	High Yield Spread			65%	63%	46%	21%	0.29	0.46
	High Yield Spread (6m_diff)			59%	59%	34%	19%	0.31	0.54
	High Yield Spread (12m_diff)			61%	69%	42%	7%	0.20	0.45
	EZ Peripheral Bond Spread			70%	60%	43%	24%	0.33	0.49
	EZ Peripheral Bond Spread (6m_diff)			81%	78%	57%	3%	0.13	0.33
	EZ Peripheral Bond Spread (12m_diff)			83%	79%	59%	4%	0.13	0.31
	MFI Loans to Private Sector (6m_ret)			56%	59%	39%	23%	0.33	0.51
	MFI Loans to Private Sector (12m_ret)			61%	57%	43%	30%	0.37	0.50
	Risk Aversion	Implied Rates Volatility			71%	68%	52%	18%	0.25
Implied Rates Volatility (6m_diff)				57%	59%	37%	23%	0.32	0.53
Implied Rates Volatility (12m_diff)				55%	53%	29%	26%	0.37	0.60
VSTOXX				62%	56%	28%	19%	0.32	0.59
VSTOXX (6m_ret)				57%	57%	27%	16%	0.30	0.59
VSTOXX (12m_ret)				60%	59%	38%	22%	0.32	0.52
VIX				67%	63%	46%	21%	0.29	0.46
VIX (6m_ret)				57%	63%	35%	13%	0.26	0.52
VIX (12m_ret)				62%	63%	43%	20%	0.29	0.48
FX Basis EUR/USD				77%	72%	66%	22%	0.25	0.31
FX Basis EUR/USD (6m_diff)				56%	63%	22%	1%	0.20	0.59
FX Basis EUR/USD (12m_diff)				66%	63%	37%	13%	0.26	0.51
Implied FX Vol				60%	63%	44%	20%	0.29	0.47
Implied FX Vol (6m_ret)				53%	57%	20%	11%	0.28	0.63
Implied FX Vol (12m_ret)				50%	56%	16%	9%	0.28	0.65
LiborOIS			65%	73%	49%	6%	0.17	0.39	
Industrial Data	Industrial Production: Industry excl. Constr. (6m_ret)			43%	57%	10%	2%	0.24	0.68
	Industrial Production: Industry excl. Constr. (12m_ret)			62%	62%	19%	0%	0.20	0.61
	Unemployment Rate			62%	44%	46%	58%	0.57	0.55
	Unemployment Rate (6m_ret)			55%	67%	38%	8%	0.21	0.48
	Unemployment Rate (12m_ret)			51%	57%	13%	4%	0.25	0.67
	Manufact. New Orders (6m_ret)			45%	61%	18%	1%	0.21	0.62
	Manufact. New Orders (12m_ret)			61%	70%	42%	4%	0.18	0.45
	Industr. Turnover: Manufacturing (6m_ret)			65%	54%	3%	0%	0.24	0.73
	Industr. Turnover: Manufacturing (12m_ret)			70%	70%	59%	20%	0.25	0.35
	MFG Stocks of Finished Products			69%	62%	51%	29%	0.34	0.44
	MFG Stocks of Finished Products (6m_diff)			58%	62%	38%	18%	0.29	0.51
	MFG Stocks of Finished Products (12m_diff)			49%	54%	3%	0%	0.24	0.73
	Retail Sales (6m_ret)			71%	69%	58%	22%	0.27	0.37
	Retail Sales (12m_ret)			69%	66%	54%	23%	0.29	0.40
	New Passenger Cars (6m_ret)			73%	69%	59%	22%	0.27	0.36
New Passenger Cars (12m_ret)			72%	69%	63%	27%	0.29	0.34	
Inflation	HICP (6m_ret)			68%	62%	61%	38%	0.38	0.39
	HICP (12m_ret)			71%	56%	58%	46%	0.45	0.43
	HICP excl. Energy, Food, Alcohol & Tobacco (6m_ret)			59%	59%	28%	30%	0.41	0.62
	HICP excl. Energy, Food, Alcohol & Tobacco (12m_ret)			55%	46%	0%	14%	0.36	0.79
	Domestic PPI: Industry excluding Construction (6m_ret)			75%	69%	66%	29%	0.30	0.33
	Domestic PPI: Industry excluding Construction (12m_ret)			79%	73%	73%	27%	0.27	0.27
Commodities	Crude Oil			79%	75%	71%	22%	0.24	0.27
	Crude Oil (6m_diff)			50%	54%	3%	0%	0.24	0.73
	Crude Oil (12m_diff)			55%	52%	30%	29%	0.39	0.59
	Gold			75%	57%	52%	39%	0.41	0.46
	Gold (6m_diff)			68%	64%	54%	28%	0.32	0.41
	Gold (12m_diff)			77%	72%	67%	24%	0.27	0.31
Wealth	ESTOXX50 (6m_ret)			62%	58%	37%	23%	0.33	0.53
	ESTOXX50 (12m_ret)			58%	57%	34%	23%	0.34	0.55
	Residential Building Permits (6m_ret)			67%	62%	48%	27%	0.33	0.46
	Residential Building Permits (12m_ret)			66%	63%	46%	22%	0.30	0.46

**Table A12: Submodel 1 - Monetary Transmission Channels over Various Time Horizons**

**6 months**

6m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued No Signal Issued	A C	B D					L= 0.25	L= 0.75
<b>Channel: Money Supply</b>				<b>95%</b>	<b>92%</b>	<b>72%</b>	<b>2%</b>	<b>0.09</b>	<b>0.21</b>
Real M1 (12m_ret)				94%	91%	70%	2%	0.09	0.23
<b>Channel: Competitiveness</b>				<b>92%</b>	<b>86%</b>	<b>65%</b>	<b>8%</b>	<b>0.15</b>	<b>0.28</b>
FX EUR/USD				81%	81%	40%	6%	0.20	0.47
Terms of Trade				38%	33%	53%	10%	0.17	0.31
<b>Channel: Sentiment</b>				<b>93%</b>	<b>90%</b>	<b>70%</b>	<b>4%</b>	<b>0.11</b>	<b>0.24</b>
PMI (12m_diff)				95%	90%	74%	5%	0.10	0.20
Economic Sentiment (6m_diff)				94%	90%	70%	3%	0.10	0.24
Industrial Confidence (6m_diff)				92%	89%	65%	4%	0.12	0.27
Business Climate (6m_diff)				93%	89%	65%	4%	0.12	0.27
Consumer Economic Situation (12m_diff)				89%	87%	65%	6%	0.13	0.28
Consumer Confidence (6m_diff)				89%	88%	63%	5%	0.13	0.29
<b>Channel: Refinancing</b>				<b>89%</b>	<b>88%</b>	<b>56%</b>	<b>3%</b>	<b>0.13</b>	<b>0.34</b>
Corporate Bonds: Investment Grade Spread				91%	85%	51%	5%	0.16	0.38
EZ Peripheral Bond Spread (12m_diff)				83%	82%	30%	3%	0.20	0.53
High Yield Spread (12m_diff)				80%	90%	58%	1%	0.11	0.32
<b>Channel: Preference for Risk</b>				<b>93%</b>	<b>88%</b>	<b>60%</b>	<b>4%</b>	<b>0.13</b>	<b>0.31</b>
LiborOIS				90%	87%	51%	2%	0.14	0.37
Implied Rates Volatility				83%	81%	35%	6%	0.20	0.50
FX Basis EUR/USD				80%	82%	40%	6%	0.19	0.47
<b>Channel: Industrial Data</b>				<b>95%</b>	<b>90%</b>	<b>72%</b>	<b>4%</b>	<b>0.10</b>	<b>0.22</b>
Retail Sales (6m_ret)				90%	86%	51%	4%	0.15	0.38
MFG Stocks of Finished Products (6m_diff)				85%	86%	47%	3%	0.15	0.41
New Passenger Cars (12m_ret)				80%	81%	33%	5%	0.21	0.52
<b>Channel: Inflation</b>				<b>86%</b>	<b>87%</b>	<b>49%</b>	<b>2%</b>	<b>0.14</b>	<b>0.39</b>
HICP (12m_ret)				86%	86%	37%	0%	0.16	0.47
Domestic PPI: Industry excluding Construction (12m_ret)				78%	81%	28%	3%	0.20	0.55
<b>Channel: Commodities</b>				<b>83%</b>	<b>85%</b>	<b>42%</b>	<b>2%</b>	<b>0.16</b>	<b>0.44</b>
Crude Oil				82%	80%	37%	8%	0.21	0.49
Gold				76%	88%	51%	1%	0.13	0.37

**18 months**

18m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued No Signal Issued	A C	B D					L= 0.25	L= 0.75
<b>Channel: Money Supply</b>				<b>90%</b>	<b>81%</b>	<b>75%</b>	<b>15%</b>	<b>0.17</b>	<b>0.23</b>
Real M1 (12m_ret)				90%	81%	75%	15%	0.17	0.23
<b>Channel: Competitiveness</b>				<b>85%</b>	<b>74%</b>	<b>66%</b>	<b>20%</b>	<b>0.24</b>	<b>0.31</b>
FX EUR/USD				82%	70%	54%	20%	0.27	0.40
Terms of Trade				82%	74%	66%	20%	0.24	0.31
<b>Channel: Sentiment</b>				<b>69%</b>	<b>76%</b>	<b>48%</b>	<b>6%</b>	<b>0.18</b>	<b>0.41</b>
PMI (12m_diff)				78%	74%	51%	12%	0.21	0.40
Economic Sentiment (6m_diff)				73%	75%	51%	9%	0.19	0.39
Industrial Confidence (6m_diff)				70%	74%	45%	7%	0.19	0.43
Business Climate (6m_diff)				71%	74%	45%	8%	0.20	0.44
Consumer Economic Situation (12m_diff)				69%	70%	45%	14%	0.24	0.45
Consumer Confidence (6m_diff)				71%	71%	45%	12%	0.23	0.44
<b>Channel: Refinancing</b>				<b>83%</b>	<b>83%</b>	<b>66%</b>	<b>6%</b>	<b>0.13</b>	<b>0.27</b>
Corporate Bonds: Investment Grade Spread				82%	83%	69%	8%	0.14	0.26
EZ Peripheral Bond Spread (12m_diff)				88%	81%	55%	3%	0.13	0.34
High Yield Spread (12m_diff)				68%	76%	45%	5%	0.17	0.43
<b>Channel: Preference for Risk</b>				<b>79%</b>	<b>81%</b>	<b>61%</b>	<b>6%</b>	<b>0.15</b>	<b>0.31</b>
LiborOIS				75%	79%	55%	6%	0.16	0.35
Implied Rates Volatility				74%	74%	51%	11%	0.21	0.40
FX Basis EUR/USD				77%	71%	55%	19%	0.25	0.38
<b>Channel: Industrial Data</b>				<b>82%</b>	<b>79%</b>	<b>60%</b>	<b>9%</b>	<b>0.17</b>	<b>0.33</b>
Retail Sales (6m_ret)				75%	71%	48%	14%	0.23	0.43
MFG Stocks of Finished Products (6m_diff)				69%	71%	43%	11%	0.23	0.45
New Passenger Cars (12m_ret)				80%	75%	54%	12%	0.21	0.38
<b>Channel: Inflation</b>				<b>81%</b>	<b>71%</b>	<b>58%</b>	<b>21%</b>	<b>0.26</b>	<b>0.37</b>
HICP (12m_ret)				75%	67%	52%	23%	0.29	0.42
Domestic PPI: Industry excluding Construction (12m_ret)				81%	70%	57%	22%	0.27	0.38
<b>Channel: Commodities</b>				<b>83%</b>	<b>74%</b>	<b>70%</b>	<b>23%</b>	<b>0.25</b>	<b>0.28</b>
Crude Oil				79%	74%	61%	19%	0.24	0.34
Gold				76%	65%	49%	25%	0.31	0.44

**24 months**

24m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued No Signal Issued	A C	B D					L= 0.25	L= 0.75
<b>Channel: Money Supply</b>				<b>79%</b>	<b>72%</b>	<b>76%</b>	<b>31%</b>	<b>0.29</b>	<b>0.26</b>
Real M1 (12m_ret)				81%	73%	77%	30%	0.28	0.25
<b>Channel: Competitiveness</b>				<b>84%</b>	<b>73%</b>	<b>73%</b>	<b>28%</b>	<b>0.27</b>	<b>0.27</b>
FX EUR/USD				84%	72%	70%	27%	0.28	0.29
Terms of Trade				79%	70%	68%	28%	0.29	0.31
<b>Channel: Sentiment</b>				<b>58%</b>	<b>64%</b>	<b>47%</b>	<b>20%</b>	<b>0.28</b>	<b>0.45</b>
PMI (12m_diff)				66%	66%	52%	22%	0.29	0.42
Economic Sentiment (6m_diff)				62%	64%	49%	23%	0.30	0.44
Industrial Confidence (6m_diff)				59%	68%	46%	12%	0.23	0.44
Business Climate (6m_diff)				59%	67%	46%	14%	0.24	0.44
Consumer Economic Situation (12m_diff)				60%	61%	43%	23%	0.32	0.49
Consumer Confidence (6m_diff)				63%	61%	41%	21%	0.31	0.50
<b>Channel: Refinancing</b>				<b>76%</b>	<b>76%</b>	<b>59%</b>	<b>10%</b>	<b>0.18</b>	<b>0.33</b>
Corporate Bonds: Investment Grade Spread				79%	82%	73%	10%	0.14	0.22
EZ Peripheral Bond Spread (12m_diff)				83%	79%	59%	4%	0.13	0.31
High Yield Spread (12m_diff)				61%	69%	42%	7%	0.20	0.45
<b>Channel: Preference for Risk</b>				<b>75%</b>	<b>77%</b>	<b>65%</b>	<b>12%</b>	<b>0.18</b>	<b>0.30</b>
LiborOIS				65%	73%	49%	6%	0.17	0.39
Implied Rates Volatility				71%	68%	52%	18%	0.25	0.41
FX Basis EUR/USD				77%	72%	66%	22%	0.25	0.31
<b>Channel: Industrial Data</b>				<b>69%</b>	<b>72%</b>	<b>58%</b>	<b>17%</b>	<b>0.23</b>	<b>0.35</b>
Retail Sales (6m_ret)				71%	69%	58%	22%	0.27	0.37
MFG Stocks of Finished Products (6m_diff)				58%	62%	38%	18%	0.29	0.51
New Passenger Cars (12m_ret)				72%	69%	63%	27%	0.29	0.34
<b>Channel: Inflation</b>				<b>78%</b>	<b>73%</b>	<b>73%</b>	<b>28%</b>	<b>0.27</b>	<b>0.27</b>
HICP (12m_ret)				71%	56%	58%	46%	0.45	0.43
Domestic PPI: Industry excluding Construction (12m_ret)				79%	73%	73%	27%	0.27	0.27
<b>Channel: Commodities</b>				<b>83%</b>	<b>79%</b>	<b>82%</b>	<b>23%</b>	<b>0.22</b>	<b>0.19</b>
Crude Oil				79%	75%	71%	22%	0.24	0.27
Gold				75%	57%	52%	39%	0.41	0.46

**Table A13: Submodel 2 - Bivariate Specification over Various Time Horizons**

**6 months**

6m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C )	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued	A	B					L= 0.25	L= 0.75
	No Signal Issued	C	D						
Single Indicators	Real M1 (12m_ret) & PMI (12m_diff)			99%	95%	84%	2%	0.06	0.13
	Real M1 (12m_ret) & Investment Grade Spreads			98%	94%	84%	3%	0.07	0.13
	Real M1 (12m_ret) & Terms of Trade			95%	91%	72%	3%	0.09	0.22
	Real M1 (12m_ret) & Retail Sales (6m_ret)			99%	94%	81%	3%	0.07	0.15
	Real M1 (12m_ret) & Crude Oil			94%	91%	70%	3%	0.10	0.23
	PMI (12m_diff) & Investment Grade Spreads			98%	93%	77%	2%	0.07	0.18
	PMI (12m_diff) & Terms of Trade			100%	98%	93%	1%	0.02	0.05
	PMI (12m_diff) & Retail Sales (6m_ret)			97%	91%	81%	6%	0.09	0.15
	PMI (12m_diff) & Crude Oil			100%	97%	93%	1%	0.03	0.06
	Corporate Investment Grade Spreads & Terms of Trade			95%	91%	79%	5%	0.09	0.17
	Corporate Investment Grade Spreads & Retail Sales (6m_ret)			95%	88%	63%	4%	0.12	0.29
	Corporate Investment Grade Spreads & Crude Oil			96%	91%	79%	5%	0.09	0.17
	Terms of Trade & Retail Sales (6m_ret)			96%	90%	74%	5%	0.10	0.20
	Terms of Trade & Crude Oil			88%	83%	65%	12%	0.18	0.29
	Retail Sales (6m_ret) & Crude Oil			94%	88%	70%	6%	0.12	0.24
	Channels: Money Supply & Industrial			99%	97%	93%	2%	0.03	0.06
	Channels: Money Supply & Refinancing			98%	93%	79%	3%	0.07	0.16
	Channels: Money Supply & Competitiveness			96%	92%	72%	2%	0.09	0.21
	Channels: Money Supply & Sentiment			100%	96%	88%	1%	0.04	0.09
	Channels: Money Supply & Commodities			95%	92%	72%	2%	0.09	0.21
Channels: Industrial & Refinancing			97%	91%	77%	4%	0.09	0.18	
Channels: Industrial & Competitiveness			99%	94%	88%	4%	0.06	0.10	
Channels: Industrial & Sentiment			96%	93%	84%	4%	0.07	0.13	
Channels: Industrial & Commodities			98%	93%	86%	5%	0.07	0.12	
Channels: Refinancing & Competitiveness			98%	92%	79%	4%	0.08	0.17	
Channels: Refinancing & Sentiment			95%	91%	74%	3%	0.09	0.20	
Channels: Refinancing & Commodities			97%	91%	79%	5%	0.09	0.17	
Channels: Competitiveness & Sentiment			100%	98%	95%	1%	0.02	0.04	
Channels: Competitiveness & Commodities			94%	87%	70%	8%	0.14	0.25	
Channels: Sentiment & Commodities			100%	100%	100%	0%	0.00	0.00	

**18 months**

18m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C )	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued	A	B					L= 0.25	L= 0.75
	No Signal Issued	C	D						
Single Indicators	Real M1 (12m_ret) & PMI (12m_diff)			92%	87%	78%	7%	0.11	0.19
	Real M1 (12m_ret) & Investment Grade Spreads			93%	83%	93%	10%	0.06	0.13
	Real M1 (12m_ret) & Terms of Trade			92%	79%	73%	18%	0.20	0.25
	Real M1 (12m_ret) & Retail Sales (6m_ret)			91%	82%	73%	12%	0.16	0.23
	Real M1 (12m_ret) & Crude Oil			90%	81%	75%	16%	0.18	0.23
	PMI (12m_diff) & Investment Grade Spreads			85%	85%	69%	6%	0.12	0.25
	PMI (12m_diff) & Terms of Trade			89%	79%	66%	13%	0.18	0.29
	PMI (12m_diff) & Retail Sales (6m_ret)			79%	79%	63%	10%	0.17	0.31
	PMI (12m_diff) & Crude Oil			89%	81%	75%	16%	0.18	0.23
	Corporate Investment Grade Spreads & Terms of Trade			88%	88%	75%	8%	0.17	0.23
	Corporate Investment Grade Spreads & Retail Sales (6m_ret)			82%	85%	75%	8%	0.13	0.21
	Corporate Investment Grade Spreads & Crude Oil			89%	77%	69%	24%	0.23	0.22
	Terms of Trade & Retail Sales (6m_ret)			86%	78%	70%	18%	0.21	0.27
	Terms of Trade & Crude Oil			83%	75%	64%	19%	0.23	0.31
	Retail Sales (6m_ret) & Crude Oil			84%	74%	67%	21%	0.24	0.30
	Channels: Money Supply & Industrial			91%	84%	75%	10%	0.14	0.22
	Channels: Money Supply & Refinancing			93%	85%	70%	6%	0.12	0.24
	Channels: Money Supply & Competitiveness			92%	81%	78%	17%	0.18	0.21
	Channels: Money Supply & Sentiment			90%	87%	76%	6%	0.11	0.20
	Channels: Money Supply & Commodities			92%	79%	76%	19%	0.20	0.23
Channels: Industrial & Refinancing			87%	86%	70%	5%	0.11	0.24	
Channels: Industrial & Competitiveness			92%	81%	75%	16%	0.18	0.23	
Channels: Industrial & Sentiment			82%	80%	63%	9%	0.16	0.30	
Channels: Industrial & Commodities			93%	85%	78%	10%	0.13	0.19	
Channels: Refinancing & Competitiveness			93%	86%	76%	7%	0.12	0.20	
Channels: Refinancing & Sentiment			83%	83%	66%	6%	0.13	0.27	
Channels: Refinancing & Commodities			94%	88%	81%	7%	0.10	0.16	
Channels: Competitiveness & Sentiment			91%	81%	70%	15%	0.19	0.26	
Channels: Competitiveness & Commodities			85%	75%	67%	20%	0.23	0.30	
Channels: Sentiment & Commodities			92%	82%	75%	13%	0.16	0.22	

**24 months**

24m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive vs. False Positive Rate	(A+D)/(A+B+C+D)	A / ( A + C )	A / (B+D)	L = f * (Type2Error) + (1 - f) *	
	Signal Issued	A	B					L= 0.25	L= 0.75
	No Signal Issued	C	D						
Single Indicators	Real M1 (12m_ret) & PMI (12m_diff)			80%	72%	76%	32%	0.30	0.26
	Real M1 (12m_ret) & Investment Grade Spreads			85%	74%	67%	20%	0.23	0.30
	Real M1 (12m_ret) & Terms of Trade			86%	77%	77%	23%	0.23	0.23
	Real M1 (12m_ret) & Retail Sales (6m_ret)			82%	73%	71%	24%	0.26	0.28
	Real M1 (12m_ret) & Crude Oil			85%	73%	67%	22%	0.25	0.30
	PMI (12m_diff) & Investment Grade Spreads			79%	83%	73%	9%	0.13	0.22
	PMI (12m_diff) & Terms of Trade			81%	66%	59%	28%	0.31	0.37
	PMI (12m_diff) & Retail Sales (6m_ret)			70%	69%	57%	21%	0.27	0.38
	PMI (12m_diff) & Crude Oil			82%	69%	62%	24%	0.28	0.35
	Corporate Investment Grade Spreads & Terms of Trade			85%	74%	71%	23%	0.25	0.28
	Corporate Investment Grade Spreads & Retail Sales (6m_ret)			79%	82%	73%	10%	0.14	0.22
	Corporate Investment Grade Spreads & Crude Oil			88%	76%	77%	26%	0.25	0.23
	Terms of Trade & Retail Sales (6m_ret)			83%	69%	62%	26%	0.29	0.35
	Terms of Trade & Crude Oil			82%	72%	68%	24%	0.26	0.30
	Retail Sales (6m_ret) & Crude Oil			82%	72%	70%	27%	0.28	0.29
	Channels: Money Supply & Industrial			80%	71%	73%	31%	0.30	0.28
	Channels: Money Supply & Refinancing			82%	79%	62%	7%	0.14	0.30
	Channels: Money Supply & Competitiveness			86%	75%	75%	26%	0.25	0.25
	Channels: Money Supply & Sentiment			79%	72%	75%	31%	0.30	0.27
	Channels: Money Supply & Commodities			87%	76%	75%	23%	0.24	0.25
Channels: industrial & Refinancing			75%	77%	59%	8%	0.16	0.32	
Channels: Industrial & Competitiveness			86%	72%	68%	26%	0.27	0.30	
Channels: Industrial & Sentiment			70%	70%	62%	22%	0.26	0.34	
Channels: Industrial & Commodities			87%	75%	73%	23%	0.24	0.26	
Channels: Refinancing & Competitiveness			89%	74%	70%	22%	0.24	0.28	
Channels: Refinancing & Sentiment			83%	76%	58%	9%	0.17	0.34	
Channels: Refinancing & Commodities			91%	76%	75%	22%	0.23	0.25	
Channels: Competitiveness & Sentiment			86%	71%	68%	27%	0.28	0.30	
Channels: Competitiveness & Commodities			84%	75%	76%	27%	0.26	0.25	
Channels: Sentiment & Commodities			87%	74%	73%	26%	0.26	0.26	

**Table A14: Submodel 3 - Unstable Surges over Various Time Horizons**

**6 months**

6m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive rate vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued	A	B					L = 0.25	L = 0.75
	No Signal Issued	C	D						
Money Supply	Real M1 & HP_Diff Lag (t0)			97%	93%	84%	5%	0.08	0.13
	Real M1 & HP_Diff Lag (t-1yr)			100%	96%	93%	3%	0.04	0.06
	Real M1 & HP_Diff Lag (t-2yr)			94%	91%	70%	3%	0.10	0.23
	Single Indicator: Real M1 (12m_ret)			94%	91%	70%	2%	0.09	0.23
Equity Markets	ESTOXX50 (12m_ret) & HP_Diff Lag (t0)			76%	80%	26%	4%	0.22	0.57
	ESTOXX50 (12m_ret) & HP_Diff Lag (t-1yr)			77%	78%	21%	6%	0.24	0.61
	ESTOXX50 (12m_ret) & HP_Diff Lag (t-2yr)			78%	80%	33%	6%	0.22	0.52
	Single Indicator: ESTOXX50 (12m_ret)			77%	78%	21%	6%	0.24	0.61
Building Permits	Residential Building Permits (6m_ret) & HP_Diff Lag (t0)			86%	82%	47%	8%	0.19	0.42
	Residential Building Permits (6m_ret) & HP_Diff Lag (t-1yr)			82%	84%	42%	3%	0.17	0.44
	Residential Building Permits (6m_ret) & HP_Diff Lag (t-2yr)			81%	84%	44%	4%	0.17	0.43
	Single Indicator: Residential Building Permits (6m_ret)			78%	84%	40%	3%	0.17	0.46
Sentiment	PMI (12m_diff) & HP_Diff Lag (t0)			97%	91%	81%	6%	0.09	0.15
	PMI (12m_diff) & HP_Diff Lag (t-1yr)			95%	90%	74%	5%	0.10	0.20
	PMI (12m_diff) & HP_Diff Lag (t-2yr)			94%	92%	74%	3%	0.08	0.20
	Single Indicator: PMI (12m_diff)			95%	90%	74%	5%	0.10	0.20
Inflation	HICP (12m_ret) & HP_Diff Lag (t0)			86%	86%	37%	0%	0.16	0.47
	HICP (12m_ret) & HP_Diff Lag (t-1yr)			95%	91%	77%	4%	0.09	0.18
	HICP (12m_ret) & HP_Diff Lag (t-2yr)			86%	86%	47%	2%	0.15	0.41
	Single Indicator: HICP (12m_ret)			86%	86%	37%	0%	0.16	0.47
Retail	Retail Sales (6m_ret) & HP_Diff Lag (t0)			94%	88%	74%	8%	0.13	0.21
	Retail Sales (6m_ret) & HP_Diff Lag (t-1yr)			91%	87%	53%	3%	0.14	0.36
	Retail Sales (6m_ret) & HP_Diff Lag (t-2yr)			91%	86%	49%	3%	0.15	0.39
	Single Indicator: Retail Sales (6m_ret)			90%	86%	51%	4%	0.15	0.38
Credit Dynamics	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t0)			82%	84%	42%	3%	0.17	0.44
	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-1yr)			77%	77%	23%	7%	0.24	0.59
	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-2yr)			61%	79%	9%	0%	0.23	0.68
	Single Indicator: MFI Loans to Private Sector (12m_ret)			54%	77%	0%	0%	0.25%	0.75%
Oil	Crude Oil & HP_Diff Lag (t0)			89%	81%	53%	10%	0.19	0.37
	Crude Oil & HP_Diff Lag (t-1yr)			84%	76%	37%	12%	0.25	0.50
	Crude Oil & HP_Diff Lag (t-2yr)			85%	81%	42%	8%	0.20	0.46
	Single Indicator: Crude Oil			82%	80%	37%	8%	0.21	0.49
Central Bank Policy	3m EURIBOR (12m_diff) & HP_Diff Lag (t0)			58%	77%	0%	0%	0.25	0.75
	3m EURIBOR (12m_diff) & HP_Diff Lag (t-1yr)			95%	89%	72%	6%	0.12	0.22
	3m EURIBOR (12m_diff) & HP_Diff Lag (t-2yr)			54%	77%	0%	0%	0.25	0.75
	Single Indicator: 3m EURIBOR			62%	77%	0%	0%	0.25	0.75

**18 months**

18m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive rate vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued	A	B					L = 0.25	L = 0.75
	No Signal Issued	C	D						
Money Supply	Real M1 & HP_Diff Lag (t0)			94%	83%	79%	15%	0.16	0.19
	Real M1 & HP_Diff Lag (t-1yr)			90%	85%	82%	14%	0.15	0.17
	Real M1 & HP_Diff Lag (t-2yr)			90%	77%	72%	20%	0.22	0.26
	Single Indicator: Real M1 (12m_ret)			90%	81%	75%	15%	0.17	0.23
Equity Markets	ESTOXX50 (12m_ret) & HP_Diff Lag (t0)			64%	62%	25%	16%	0.30	0.60
	ESTOXX50 (12m_ret) & HP_Diff Lag (t-1yr)			66%	65%	36%	17%	0.29	0.52
	ESTOXX50 (12m_ret) & HP_Diff Lag (t-2yr)			65%	61%	21%	14%	0.30	0.63
	Single Indicator: ESTOXX50 (12m_ret)			65%	60%	24%	18%	0.32	0.61
Building Permits	Residential Building Permits (6m_ret) & HP_Diff Lag (t0)			91%	79%	61%	9%	0.17	0.31
	Residential Building Permits (6m_ret) & HP_Diff Lag (t-1yr)			74%	71%	51%	17%	0.25	0.41
	Residential Building Permits (6m_ret) & HP_Diff Lag (t-2yr)			70%	70%	39%	13%	0.25	0.49
	Single Indicator: Residential Building Permits (6m_ret)			69%	67%	40%	16%	0.27	0.49
Sentiment	PMI (12m_diff) & HP_Diff Lag (t0)			89%	84%	76%	11%	0.14	0.21
	PMI (12m_diff) & HP_Diff Lag (t-1yr)			81%	76%	63%	16%	0.21	0.32
	PMI (12m_diff) & HP_Diff Lag (t-2yr)			81%	75%	57%	13%	0.21	0.36
	Single Indicator: PMI (12m_diff)			78%	74%	51%	12%	0.21	0.40
Inflation	HICP (12m_ret) & HP_Diff Lag (t0)			75%	66%	53%	2%	0.31	0.42
	HICP (12m_ret) & HP_Diff Lag (t-1yr)			75%	68%	52%	22%	0.29	0.41
	HICP (12m_ret) & HP_Diff Lag (t-2yr)			75%	70%	52%	19%	0.27	0.41
	Single Indicator: HICP (12m_ret)			75%	67%	52%	23%	0.29	0.42
Retail	Retail Sales (6m_ret) & HP_Diff Lag (t0)			86%	83%	79%	14%	0.16	0.19
	Retail Sales (6m_ret) & HP_Diff Lag (t-1yr)			76%	73%	46%	12%	0.22	0.41
	Retail Sales (6m_ret) & HP_Diff Lag (t-2yr)			75%	72%	46%	12%	0.22	0.43
	Single Indicator: Retail Sales (6m_ret)			75%	71%	48%	14%	0.23	0.43
Credit Dynamics	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t0)			74%	70%	45%	14%	0.24	0.45
	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-1yr)			62%	75%	42%	4%	0.17	0.45
	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-2yr)			61%	59%	13%	12%	0.31	0.68
	Single Indicator: MFI Loans to Private Sector (12m_ret)			60%	68%	30%	8%	0.24	0.55
Oil	Crude Oil & HP_Diff Lag (t0)			88%	73%	64%	2%	0.26	0.32
	Crude Oil & HP_Diff Lag (t-1yr)			80%	71%	58%	20%	0.26	0.36
	Crude Oil & HP_Diff Lag (t-2yr)			80%	74%	61%	19%	0.24	0.34
	Single Indicator: Crude Oil			79%	74%	61%	19%	0.24	0.34
Central Bank Policy	3m EURIBOR (12m_diff) & HP_Diff Lag (t0)			72%	77%	46%	4%	0.16	0.41
	3m EURIBOR (12m_diff) & HP_Diff Lag (t-1yr)			81%	81%	55%	4%	0.14	0.35
	3m EURIBOR (12m_diff) & HP_Diff Lag (t-2yr)			66%	74%	36%	2%	0.17	0.49
	Single Indicator: 3m EURIBOR			65%	69%	39%	13%	0.25	0.49

**24 months**

24m Forecasting Horizon				AUROC	Correct Signal	Crisis Detected	False Alarm	Risk-Affine	Risk-Averse
Transmission Channel	Classification	Recession	No Recession	True positive rate vs. False Positive Rate	(A+D)/(A+B+C+D)	A / (A + C)	A / (B+D)	L = f * (Type2Error) + (1 - f) * (Type1Error)	
	Signal Issued	A	B					L = 0.25	L = 0.75
	No Signal Issued	C	D						
Money Supply	Real M1 & HP_Diff Lag (t0)			88%	79%	82%	24%	0.23	0.19
	Real M1 & HP_Diff Lag (t-1yr)			82%	73%	77%	31%	0.29	0.25
	Real M1 & HP_Diff Lag (t-2yr)			81%	73%	77%	31%	0.29	0.25
	Single Indicator: Real M1 (12m_ret)			81%	73%	77%	30%	0.28	0.25
Equity Markets	ESTOXX50 (12m_ret) & HP_Diff Lag (t0)			61%	56%	33%	24%	0.35	0.56
	ESTOXX50 (12m_ret) & HP_Diff Lag (t-1yr)			57%	59%	38%	23%	0.33	0.52
	ESTOXX50 (12m_ret) & HP_Diff Lag (t-2yr)			58%	57%	35%	24%	0.34	0.55
	Single Indicator: ESTOXX50 (12m_ret)			58%	57%	34%	23%	0.34	0.55
Building Permits	Residential Building Permits (6m_ret) & HP_Diff Lag (t0)			92%	86%	77%	7%	0.11	0.19
	Residential Building Permits (6m_ret) & HP_Diff Lag (t-1yr)			69%	64%	53%	27%	0.32	0.42
	Residential Building Permits (6m_ret) & HP_Diff Lag (t-2yr)			68%	62%	52%	29%	0.34	0.43
	Single Indicator: Residential Building Permits (6m_ret)			67%	62%	48%	27%	0.33	0.46
Sentiment	PMI (12m_diff) & HP_Diff Lag (t0)			89%	77%	78%	24%	0.24	0.21
	PMI (12m_diff) & HP_Diff Lag (t-1yr)			64%	63%	53%	23%	0.29	0.41
	PMI (12m_diff) & HP_Diff Lag (t-2yr)			63%	64%	48%	21%	0.29	0.44
	Single Indicator: PMI (12m_diff)			66%	66%	52%	22%	0.29	0.42
Inflation	HICP (12m_ret) & HP_Diff Lag (t0)			71%	57%	72%	57%	0.49	0.35
	HICP (12m_ret) & HP_Diff Lag (t-1yr)			71%	57%	62%	48%	0.45	0.40
	HICP (12m_ret) & HP_Diff Lag (t-2yr)			71%	56%	59%	47%	0.45	0.42
	Single Indicator: HICP (12m_ret)			71%	56%	58%	46%	0.45	0.43
Retail	Retail Sales (6m_ret) & HP_Diff Lag (t0)			88%	83%	80%	14%	0.16	0.19
	Retail Sales (6m_ret) & HP_Diff Lag (t-1yr)			71%	69%	59%	22%	0.27	0.36
	Retail Sales (6m_ret) & HP_Diff Lag (t-2yr)			71%	68%	58%	23%	0.28	0.37
	Single Indicator: Retail Sales (6m_ret)			71%	69%	58%	22%	0.27	0.37
Credit Dynamics	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t0)			70%	66%	58%	28%	0.31	0.38
	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-1yr)			64%	60%	48%	29%	0.35	0.46
	MFI Loans to Private Sector (12m_ret) & HP_Diff Lag (t-2yr)			60%	57%	43%	31%	0.38	0.50
	Single Indicator: MFI Loans to Private Sector (12m_ret)			61%	57%	43%	30%	0.37	0.50
Oil	Crude Oil & HP_Diff Lag (t0)			86%	80%	85%	2%	0.21	0.17
	Crude Oil & HP_Diff Lag (t-1yr)			79%	75%	72%	22%	0.24	0.26
	Crude Oil & HP_Diff Lag (t-2yr)			79%	73%	67%	22%	0.25	0.30
	Single Indicator: Crude Oil			79%	75%	71%	22%	0.24	0.27
Central Bank Policy	3m EURIBOR (12m_diff) & HP_Diff Lag (t0)			70%	75%	65%	16%	0.21	0.30
	3m EURIBOR (12m_diff) & HP_Diff Lag (t-1yr)			66%	72%	58%	16%	0.22	0.35
	3m EURIBOR (12m_diff) & HP_Diff Lag (t-2yr)			68%	69%	61%	23%	0.27	0.35
	Single Indicator: 3m EURIBOR			63%	59%	42%	27%	0.35	0.50