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Vulnerable growth in the Euro Area: Measuring the financial conditions

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Abstract

This paper examines which measures of financial conditions are informative about the tail risks to output growth in the euro area. The Composite Indicator of Systemic Stress (CISS) is more informative than indicators focusing on narrower segments of financial markets or their simple aggregation in the principal component. Conditionally on the CISS one can reproduce for the euro area the stylized facts known from the US, such as the strong negative correlation between conditional mean and conditional variance that generates stable upper quantiles and volatile lower quantiles of output growth.

Keywords: downside risk, macro-financial linkages, quantile regression
JEL codes: C12, E37, E44.

Non-technical Summary

A growing number of studies starting with Adrian et al. (2019) examine the relation between financial conditions and tail risks to output growth. This research finds that bad realizations of output growth are more severe after episodes of tight financial conditions. The present paper studies the relation between financial conditions and tail risks to output growth in the aggregate euro area data.

The challenge is that in the euro area there is less experience in measuring financial conditions than in the US, on which most of this research has focused. First, the history of integrated European financial markets is much shorter. Second, European financial system has some distinct features. For example, it is more bank-based, with a smaller role of the corporate bond market relative to the US and it has witnessed occasional increases in the core-periphery sovereign bond spreads. Therefore, this paper compares the performance of several different measures of financial conditions for capturing the tail risks to euro area output growth.

The paper shows that the findings of Adrian et al. (2019) are also relevant for the euro area, but it is important to use an appropriate indicator of financial conditions. Some intuitive indicators that focus on specific segments of financial markets, such as the retail bank lending spread or the sovereign spread are not very useful indicators of tail risks to growth in the euro area sample. Corporate bond spreads and the stock price volatility work reasonably well and the euro area TED spread (computed as the 3-month interbank lending rate minus the 3-month German Treasury Bill yield) is the best among the narrow (segment-specific) indicators that we consider. A simple aggregation of several narrow indicators with a principal component does not necessarily yield an informative indicator of tail risks to growth. We find that the financial indicator that is most informative about tail behavior of output is the Composite Indicator of Systemic Stress (CISS) (Holló et al., 2012) which aggregates individual financial variables in a nonlinear way designed to capture the "systemic" nature of events.

Using the CISS we establish for the euro area three stylized facts analogous to those identified for the US economy by Adrian et al. (2019) and Adrian et al. (2020). First,

the left-tail of the output growth distribution comoves strongly with financial conditions, while the right-tail tends to be more stable over time. Second, the conditional means and variances of output growth are negatively correlated. Periods of financial distress (such as the Great Financial Crisis or the European Sovereign Debt Crisis) are associated with a decline in mean and an increase in variance. Third, none of these effects extends to inflation.

1 Introduction

During the recent years of economic turmoil and financial distress, policy makers' attention has been drawn towards the relation between financial conditions and output growth. In a recent paper, Adrian et al. (2019) find that financial conditions play a critical role for forecasting the distribution of future output growth in the US and in particular its downside risks. This paper applies their analysis to the euro area. The challenge is that in the euro area there is less experience in measuring financial conditions than in the US, as the history of integrated European financial markets is much shorter. It is not obvious which aspects of financial conditions are the most relevant in the euro area for the specific exercise of estimating risks to growth. Is it the stress in the corporate bond market, in the interbank lending market, retail lending conditions, the term spread, the sovereign spread or the stock market volatility? How to best aggregate these narrow indicators? To answer these questions we consider different measures of financial conditions and examine their information content about risks to output growth in the euro area.

This paper contributes to the recent literature on tail risks to growth that builds on Adrian et al. (2019), such as Brownlees and Souza (2019); Chavleishvili and Manganelli (2019); Reichlin et al. (2020). Unlike these papers, we focus on the performance of different measures of euro area financial conditions. Another related literature is the one on measuring financial conditions in the euro area, such as Holló et al. (2012); Matheson (2012); Gilchrist and Mojon (2018). Differently from these papers, we focus on tail risks.

2 Measuring European financial conditions for the estimation of risks to growth

Table 1 lists ten different indicators of euro area financial conditions that we consider in this paper.

The first three indicators measure the spreads in the corporate bond markets. The Euro High Yield bond Option-Adjusted Spread by ICE BofAML is based on the yields of euro-denominated below investment grade corporate bonds publicly issued in the euro

Table 1: Financial indicators for the euro area

Indicator	*Description*
High Yield bond spread	ICE BofAML Euro High Yield Index, Option-Adjusted Spread (FRED)
Bank bond spread	Bank bond yields minus sovereign yields for the same maturity (Gilchrist and Mojon, 2018)
NFC bond spread	NFC bond yields minus sovereign yields for the same maturity (Gilchrist and Mojon, 2018)
TED spread euro area	3-month Euribor (Reuters) minus 3-month BuBill (Bloomberg)
Retail lending spread	Lending rate to non-financial private sector (MIR database) minus 3m Euribor (Reuters)
Term spread	10-year Bund (Bundesbank) minus 3-month BuBill (Bloomberg)
Sovereign spread	Euro area 10-year sovereign yield (Haver) minus 10-year Bund yield (Bundesbank)
VSTOXX	30-day implied volatility of the EURO STOXX 50 (Bloomberg)
PC1	The first principal component of the above variables
CISS	Composite Indicator of Systemic Stress (ECB Statistical Data Warehouse, Holló et al., 2012)

domestic or eurobond markets. The Bank and Non-financial Corporations (NFC) bond spreads by Gilchrist and Mojon (2018) are based on euro-denominated corporate bonds across ratings (but dropping the spreads that exceed 30%) issued by banks and non-financial corporations respectively in Germany, France, Italy and Spain. All these three indicators measure the spread with respect to the domestic sovereign bonds of the matching maturity, thus avoiding the confounding of credit risk premia with term premia.[1]

[1]We have also used the Bank and NFC spreads with respect to the German bunds, provided by Gilchrist and Mojon (2018) as an alternative, but they yielded similar results in our analysis so we omit

The "European TED spread" reflects the credit risk for interbank loans. By analogy to the US TED spread (the spread between the 3-month Eurodollar and the 3-month Treasury), we compute it as the spread between the 3-month Euribor and the 3-month BuBill (German treasury discount paper).

The Retail lending spread measures the spread between the retail bank lending rates faced by the non-financial private sector (corporations and households) and the 3-month Euribor. We take the data from the ECB database of Monetary and financial institutions Interest Rates (MIR). A priori, the retail lending spread might be expected to be very relevant in the euro area where bank lending is more important than bond financing, but we will see that this is not necessarily the case.

The Term spread is measured as the difference between the 10-year and 3-months German sovereign bond yield. We focus on the term spread in the German sovereign bonds as they were perceived as virtually free of the default risk throughout our sample. By contrast the term spreads in some other government bond might be distorted by the perceptions of the default risk at different horizons.

The Sovereign spread reflects the riskiness of the euro area sovereign debt relative to the safest, German debt. It is the difference between the average 10-year euro area government bond yield and the 10-year German Bund yield. This is another variable specific to the euro area and potentially relevant according to the conventional wisdom.

The VSTOXX is the implied volatility of the EURO STOXX 50 index and reflects the overall level of uncertainty in financial markets.

Finally, we consider two summary measures of financial conditions. PC1 is the first principal component of the above indicators. This reflects a simple minded aggregation of the different aspects of financial conditions captured by these indicators. The second is the Composite Indicator of Systemic Stress (CISS) by Holló et al. (2012). This is a more sophisticated aggregation of indicators similar to those above. The aggregation is nonlinear and picks up the episodes when multiple indicators are simultaneously high and at the same time exhibit high time-varying correlations, with the goal to detect 'systemic' stress episodes.

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them for brevity.

Table 2: Regressions of one-year-ahead real GDP growth on alternative indicators

Indicator	*OLS*	*Q10*	*Q50*	*Q90*	*tick loss Q10*
Current RGDP growth	0.336***	0.861***	0.477***	0.145	0.35
	(0.089)	(0.310)	(0.150)	(0.132)	
High Yield bond spread	-0.138**	-0.250	-0.117***	-0.0751	0.40
	(0.0536)	(0.246)	(0.0438)	(0.0742)	
Bank bond spread	-1.487***	-1.977	-1.305***	-1.284***	0.38
	(0.359)	(1.643)	(0.399)	(0.364)	
NFC bond spread	-1.536***	-2.652	-1.135***	-1.101***	0.36
	(0.376)	(1.855)	(0.425)	(0.280)	
TED spread euro area	-2.798***	-3.943**	-2.235***	-2.173***	0.29
	(0.430)	(1.885)	(0.784)	(0.398)	
Retail lending spread	0.937**	2.495**	0.493	-0.972**	0.36
	(0.358)	(1.010)	(0.433)	(0.386)	
Term spread	0.391	0.707	0.0348	0.224	0.42
	(0.272)	(1.255)	(0.233)	(0.336)	
Sovereign spread	-0.673*	-0.817	-0.587	-1.356***	0.42
	(0.373)	(1.034)	(0.423)	(0.290)	
VSTOXX	-1.663**	-2.374	-1.262**	-1.427*	0.39
	(0.634)	(2.120)	(0.547)	(0.811)	
PC1	-0.398***	-0.409	-0.503***	-0.247***	0.38
	(0.101)	(0.291)	(0.131)	(0.0797)	
CISS	-6.612***	-16.26***	-6.624***	-2.411*	0.23
	(1.114)	(3.595)	(2.387)	(1.409)	

Notes: Columns 2-5: Slope coefficients corresponding to OLS and quantile regressions. Standard errors in parentheses are based on bootstrap with 1000 replications implemented in the Stata command sqreg. *** p<0.01, ** p<0.05, * p<0.1. Column 6: tick loss corresponding to the 10th quantile and averaged over observations.

Next, we study how each of the indicators in Table 1 relates to the GDP growth over the subsequent year. Following Adrian et al. (2019) we estimate univariate OLS and quantile regressions (see Koenker and Bassett, 1978) of the form:

$$y_{t+4} - y_t = \alpha + \beta x_t + u_t \tag{1}$$

where y_t is the log of real GDP, so $y_{t+4} - y_t$ is the one-year-ahead real GDP growth rate and x_t is either the current quarter GDP growth ($y_t - y_{t-1}$) or a financial indicator. We run the quantile regressions for the 10th, 50th and 90th quantile.[2] The samples start in $t = 1999\text{Q1}$ and end in $t = 2018\text{Q2}$ (the last left-hand-side observation is $y_{2019\text{Q2}} - y_{2018\text{Q2}}$).

Table 2 reports the estimated slope coefficients. We highlight three observations on these coefficients.

First, most of the financial indicators are negatively related to next-year output growth. The retail lending spread and the term spread are the two exceptions: their relation to next year output growth is actually positive, even if rarely statistically significant. Current output growth is also, as expected, positively related to future growth.

Second, according to the point estimates the bottom tail of the growth distribution is more sensitive to financial conditions than the higher quantiles. We conclude this from the fact that for the majority of financial indicators (with the notable exception of the sovereign spread) the coefficient of the 10th quantile is larger in absolute value (i.e., more negative) than the coefficients for the higher quantiles. However, these relations are not always statistically significant. The are only significant for the CISS and the euro area TED spread.

All these findings hold also when we use the longest available sample for each variable instead of the common sample used here and when we control for the current real GDP growth (see the Appendix).

Figure 1A illustrates the last row of Table 2, showing the scatter plot of the output growth and the CISS, along with the four regression lines. We can see that the empirical distribution of output growth spreads out and becomes more negatively skewed as the CISS increases. This is analogous to the observation of Adrian et al. (2019) on the US output growth and the NFCI. Figure 1B shows that this analogy is largely lost if we use the PC1 as a measure of euro area financial conditions.

Third, the CISS does the best job fitting the 10th quantile of GDP growth, followed by the TED spread. This is reflected in the lowest values of the "tick" loss reported in

[2]We consider the 10th and 90th quantile, not 5th and 95th as in Adrian et al. (2019), as our sample is smaller.

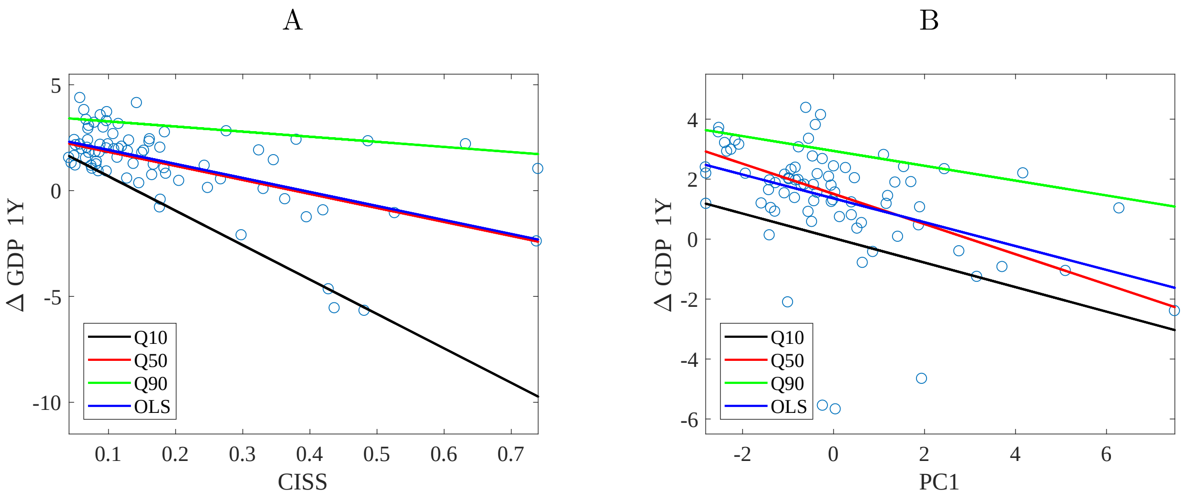

Figure 1: **Quantile Regression.** Univariate quantile regressions of one-year-ahead real GDP growth on CISS (panel A) and on PC1 (panel B).

the last column of Table 2 (0.23 and 0.29 respectively). The tick loss is the objective function that is minimized by the quantile regression. Giacomini and Komunjer (2005) argue that this is the implicit loss function whenever the object of interest is a forecast

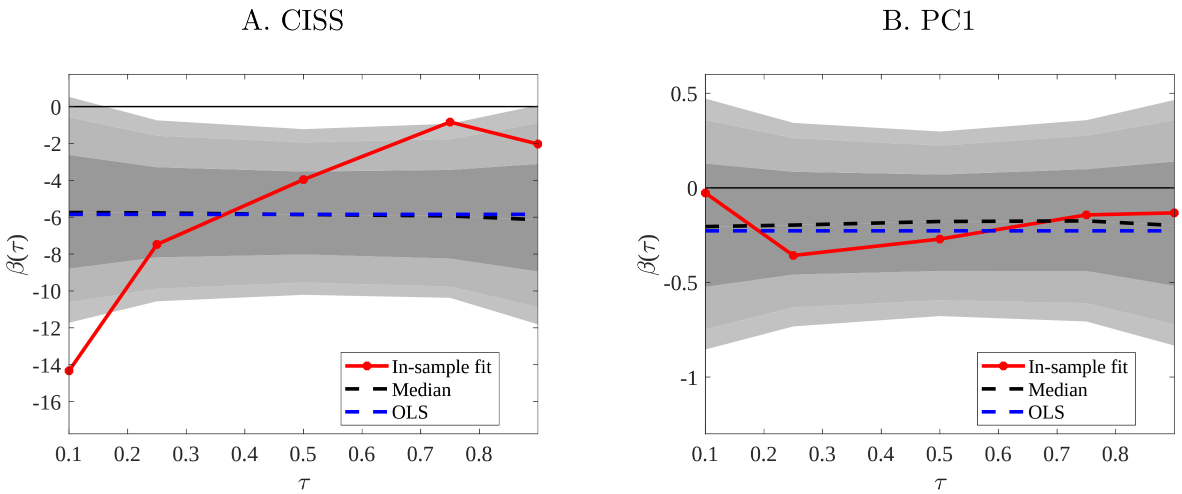

Figure 2: **Nonlinearity Test.** Coefficients of bivariate quantile regressions of one-year-ahead real GDP growth with current GDP growth and a measure of financial conditions as conditioning variables. Shaded bands indicate 68, 90 and 95 percent confidence bands under the null hypothesis of a linear data generating process: a VAR(4) with real GDP growth and financial conditions. The bands are obtained with a bootstrap procedure with 5000 replications.

of a particular quantile of a distribution.[3]

Next we test whether the quantile regression slopes differ significantly from the OLS slope using the approach proposed by Adrian et al. (2019). Figure 2A shows that the slope of the CISS corresponding to the 10th quantile is significantly different from the OLS slope at the 5 percent confidence level. So the CISS has a significantly asymmetric effect on the lower tail of the output growth. For the remaining variables we cannot reject the null that the slopes are the same (see Figure 2B for PC1 and the Appendix for the other variables).

These findings indicate that the CISS is the most informative financial indicator, from those considered here, for capturing the nonlinear relationship between financial conditions and future output growth in the euro area.[4]

3 Stylized facts on financial conditions, growth and inflation

We now take the CISS as the summary measure of the euro area financial conditions and illustrate three stylized facts analogous to those identified for the US economy by Adrian et al. (2019) and Adrian et al. (2020). We use the sample 1986Q4-2018Q2, as the CISS is available for this longer sample.

Stylized Fact 1: Financial conditions explain shifts in the lower tail of the conditional output growth distribution. The result is illustrated in Figure 3 plotting the quantiles and one-year-ahead real GDP growth over time. The lower conditional quantiles of output growth distribution vary strongly over time, while the upper quantiles are quite stable. We can see the disproportionally large drops of the bottom quantiles in the periods of financial turmoil, when the CISS was high, such as the Great Financial Crisis or the subsequent European Sovereign Debt Crisis.

Stylized Fact 2: Conditional mean and variance of output growth correlate

[3] Tick loss is computed as $(\alpha - \mathbf{1}(e_{t+1} < 0))\, e_{t+1}$ where α is the quantile of interest (here: 0.1) and e_{t+1} is the forecast error. We average it over all observations in the sample.

[4] The CISS also performs best in an out-of-sample predictive density evaluation, followed by the VSTOXX and the TED spread. See the Appendix for details.

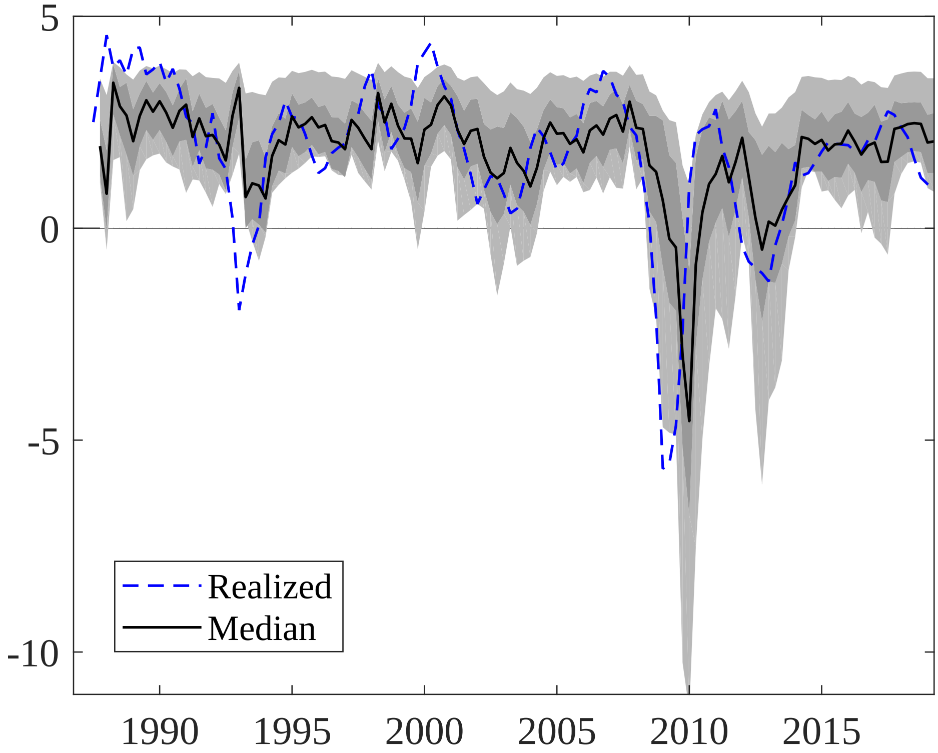

Figure 3: **Predicted Distribution of Output Growth Over Time.** Estimated conditional distribution of one-year-ahead real GDP growth based on bivariate quantile regressions with current GDP growth and CISS as conditioning variables over the sample 1986Q4-2018Q2.

negatively. To capture this fact we follow Adrian et al. (2019) and fit the skewed t-distribution of Azzalini and Capitanio (2003) into the fitted quantiles for each quarter displayed in Figure 3. Figure 4 shows the scatter plot of the conditional means against the conditional variances of these distributions, illustrating their tight negative correlation.

Stylized Fact 3: We do not observe similar effects for inflation. Figure 5 plots the quantiles of one-year-ahead core inflation (HICP excluding food and energy), showing that their behavior is very different from those in Figure 3. First, we do not find significant nonlinearity in the relation of the CISS with inflation. Second, conditional mean and variance of inflation correlate positively, not negatively as in the case of output growth, reflecting the well-known fact that when inflation is higher it also tends to be more volatile.[5]

4 Conclusions

This paper finds that the "vulnerable growth" approach of Adrian et al. (2019) is also relevant for the euro area, but it is important to use an appropriate indicator of financial conditions. Some intuitive indicators, such as the retail lending spread or the sovereign spread are not useful indicators of tail risks to growth. Bond spreads and the stock volatility work reasonably well and the euro area TED spread is the best among our individual indicators. A simple aggregation of the individual indicators with a principal component does not yield a particularly informative financial indicator for estimating risks to growth. We find that the most informative financial indicator is the CISS, which aggregates individual indicators in a nonlinear way capturing the "systemic" nature of events.

Armed with this indicator we establish for the euro area three stylized facts analogous to those identified for the US economy by Adrian et al. (2019) and Adrian et al. (2020). First, the left-tail of the output growth distribution comoves strongly with financial conditions, while the right-tail tends to be more stable over time. Second, the conditional means and variances of output growth are negatively correlated. Periods of financial distress (such as the Great Financial Crisis or the European Sovereign Debt Crisis) are associated with a decline in mean and an increase in volatility. Third, none of these effects extends to inflation.

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[5]See the Appendix for more evidence on inflation.

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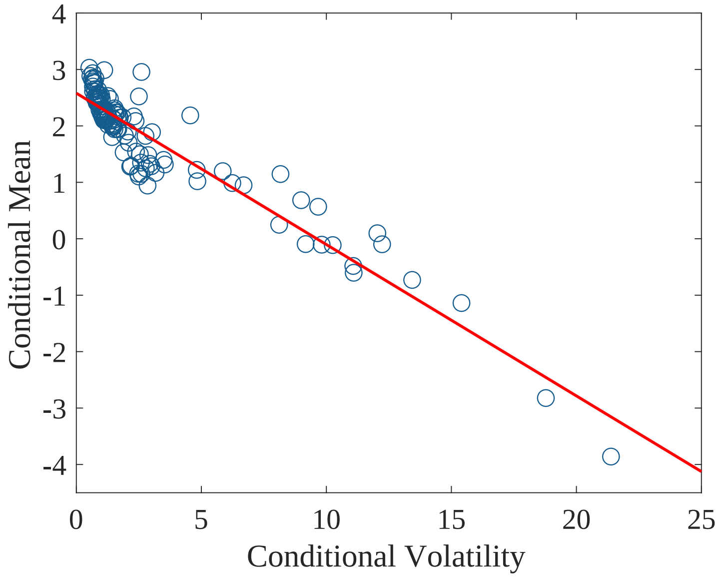


Figure 4: **Mean and Variance of the Conditional Distribution of Output Growth.** Estimated conditional distribution of one-year-ahead real GDP growth based on bivariate quantile regressions with current GDP growth and CISS as conditioning variables over the sample 1986Q4-2018Q2.

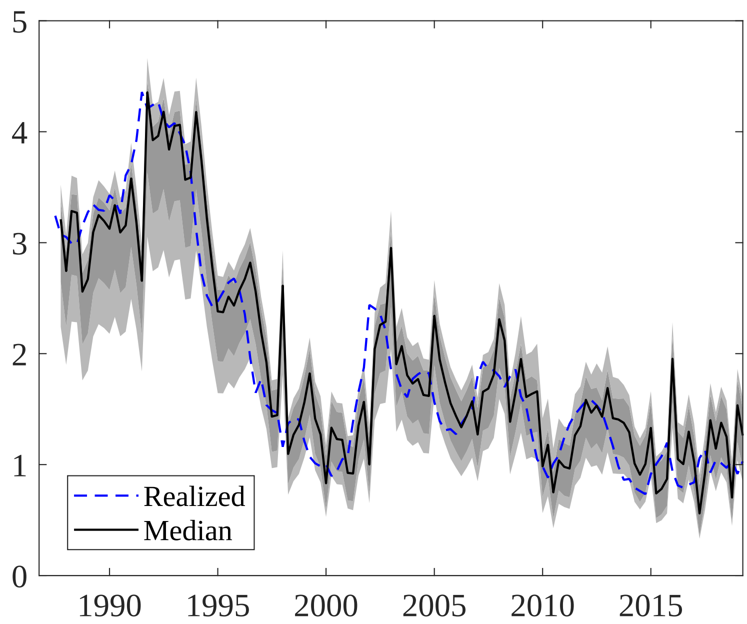


Figure 5: **Predicted Distribution of Inflation Over Time.** Estimated conditional distribution of one-year-ahead core inflation based on bivariate quantile regressions with current core inflation and CISS as conditioning variables over the sample 1986Q4-2018Q2.

Appendix

This Appendix reports additional results and robustness checks omitted in the paper for brevity.

Quantile regressions on maximum samples. Table A1 contains the estimated slope coefficients of the OLS and quantile regressions on maximum available samples for the high yield bond spread, the retail lending spread, the term spread and the CISS. For these variables we were able to extend the sample back before 1999Q1. The samples are provided in column 1. Our baseline results turn out to be robust to these changes in the samples.

Controlling for Economic Conditions. Table A2 presents the estimated coefficients for the baseline exercise controlling for current quarter GDP growth. Most of our baseline results turn out to be robust to the inclusion of current economic conditions.

Out-of-Sample Exercise. We re-estimate the quantile regressions on expanding samples, fit the skewed t-density of Azzalini and Capitanio (2003) into the estimated quantiles and evaluate the predictive density score of this density at the actually realized GDP growth one year ahead. In this exercise we control also for the current quarter GDP growth and ask whether adding a financial variable improves the forecast. The samples start in 1999Q1 to ensure that we have equal sample sizes for all variables. The first sample ends in 2007Q2 and forecasts the year-on-year growth in 2008Q2, the last sample ends in 2018Q2 and forecasts the year-on-year real GDP growth in 2019Q2. The downside of this exercise is the need to estimate quantile regressions on small samples if we want to include the forecasts for the crisis period, when the tail risks actually materialized.

Table A3 reports the mean log scores of these predictive densities. We can see that also in this exercise the CISS emerges as the best, attaining the highest log score of -3.37. The TED spread and the VSTOXX also improve on the predictive density based on current quarter GDP growth only, which is -4.88. The other variables fail to improve the log scores.

Extra Figures. Figure A1 presents the data used in the paper.

Figure A2 reports the nonlinearity test proposed by Adrian et al. (2019) for the variables other than the CISS and PC1 already reported in the main text. The results indicate that the coefficients corresponding to the bottom quantiles are not statistically different from the OLS coefficient for each of these variables. We can see that the coefficient for the bottom quantiles are always within the bootstrapped bands.

Figure A3 plots the conditional distribution of future GDP growth obtained by fitting the skewed t-density of Azzalini and Capitanio (2003) into the estimated quantiles for each quarter over the sample 1986Q4-2018Q2. We highlight two lessons from this figure that are in line with the results presented in the paper. First, the conditional distribution of future GDP growth varies over time. In particular, in some periods (e.g., the 2008 Global Financial Crisis or the 2011 European Sovereign Debt Crisis) the conditional distribution is strongly left-skewed, while in other periods the conditional distributions tend to be more symmetric. Second, while the right tail of the distribution tends to be stable, the left tail and the median vary significantly over time, thus indicating that the downside risk to GDP growth exhibits a stronger variation over time than the upside risk. These results echo the findings reported by Adrian et al. (2019) for the US economy.

Figure A4 reports the nonlinearity tests of Adrian et al. (2019) for the relationship of core inflation with financial variables. All the quantile regression coefficients are inside the 90 percent confidence bands, so we do not reject the null hypothesis that the quantile regression slopes are equal to the OLS slopes. We conclude that financial variables are not informative about tail realizations of inflation.

Figure A5 shows the relation between the conditional means and conditional volatilities of inflation. This figure substantiates our claim in the paper that the negative relation that we observe for output growth does not extend to inflation. In fact, we can see that for inflation the relation is actually positive, i.e., inflation is more volatile when it is higher.

Figure A6 illustrates the effect of the CISS on the conditional quantiles of output growth (top row) and inflation (bottom row) by comparing the conditional quantiles obtained with (left column) and without the CISS (right column). It shows that the CISS explains large shifts in the lower tail of the conditional output growth distributions. By contrast, including the CISS or not makes little discernible difference for the conditional distributions of inflation.

Table A1: Regressions of one-year-ahead real GDP growth on alternative indicators: results for longer samples

Indicator	*OLS*	*Q10*	*Q50*	*Q90*	*tick loss Q10*
High Yield bond spread	-0.133**	-0.250	-0.106**	-0.0843	0.40
(1997Q4-2018Q2)	(0.0530)	(0.195)	(0.0413)	(0.0894)	
Retail lending spread	0.00399	0.482	-0.329*	-0.577**	0.39
(1985Q1-2018Q2)	(0.205)	(0.625)	(0.188)	(0.259)	
Term spread	0.379***	0.637	0.159	0.164	0.37
(1985Q1-2018Q2)	(0.129)	(0.469)	(0.105)	(0.138)	
CISS	-6.858***	-16.17***	-7.006***	-2.836***	0.25
(1986Q4-2018Q2)	(0.979)	(3.333)	(2.290)	(0.975)	

Notes: Columns 2-5: Slope coefficients corresponding to OLS and quantile regressions. Standard errors in parentheses are based on bootstrap with 1000 replications implemented in the Stata command sqreg. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Column 6: tick loss corresponding to the 10th quantile and averaged over observations.

Table A2: Regressions of one-year-ahead real GDP growth on alternative indicators controlling for current real GDP growth

Indicator	*OLS*	*Q10*	*Q50*	*Q90*
High Yield bond spread	-0.0101	-0.0261	-0.0755	-0.0136
	(0.0655)	(0.185)	(0.0572)	(0.0919)
Bank bond spread	-0.912**	-0.0899	-0.978**	-0.971**
	(0.449)	(1.405)	(0.412)	(0.487)
NFC bond spread	-0.883*	-1.409	-0.704	-0.555
	(0.509)	(1.790)	(0.441)	(0.592)
TED spread euro area	-2.574***	-4.553**	-1.574**	-2.151***
	(0.567)	(1.999)	(0.764)	(0.709)
Retail lending spread	1.094***	1.714**	0.525	-0.854*
	(0.317)	(0.681)	(0.374)	(0.460)
Term spread	0.630**	0.804	0.274	0.269
	(0.245)	(0.811)	(0.228)	(0.343)
Sovereign spread	-0.318	0.877	-0.499	-1.031***
	(0.357)	(0.956)	(0.337)	(0.302)
VSTOXX	-0.684	-0.844	-0.750	-0.535
	(0.669)	(1.885)	(0.555)	(0.700)
PC1	-0.208	-0.0270	-0.238	-0.116
	(0.141)	(0.371)	(0.145)	(0.111)
CISS	-5.933***	-16.51***	-3.037	-1.167
	(1.536)	(3.484)	(2.305)	(1.974)

Notes: Slope coefficients corresponding to OLS and quantile regressions with current GDP growth and the listed financial indicators (entering one at a time) as conditioning variables. All samples start in 1999Q1. Standard errors in parentheses are based on bootstrap with 1000 replications implemented in the Stata command sqreg. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Predictive power of euro area financial indicators: log scores

Indicator	*Log Score*	*Indicator*	*Log Score*
Current GDP growth	-4.88	Term spread	-15.18
High Yield bond spread	-7.39	Sovereign spread	-6.25
Bank bond spread	-7.23	VSTOXX	-3.82
NFC bond spread	-5.11	PC1	-5.88
TED spread euro area	-4.36	CISS	-3.37
Retail lending spread	-9.45		

Notes: Mean log predictive density score in the pseudo out-of-sample exercise.

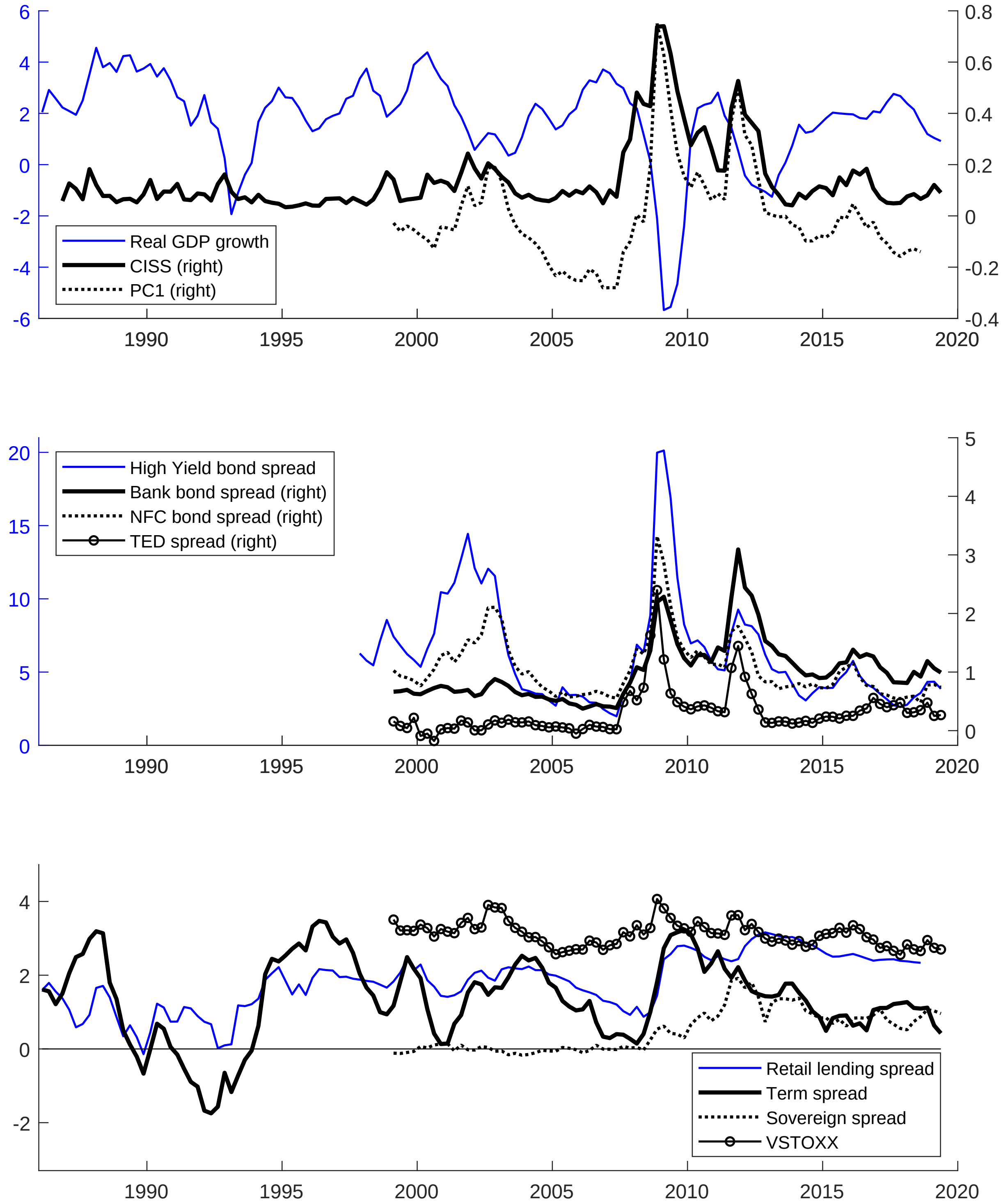


Figure A1: **Data plot.** Quarterly. Real GDP is in year-on-year growth rates $(y_t - y_{t-4})$.

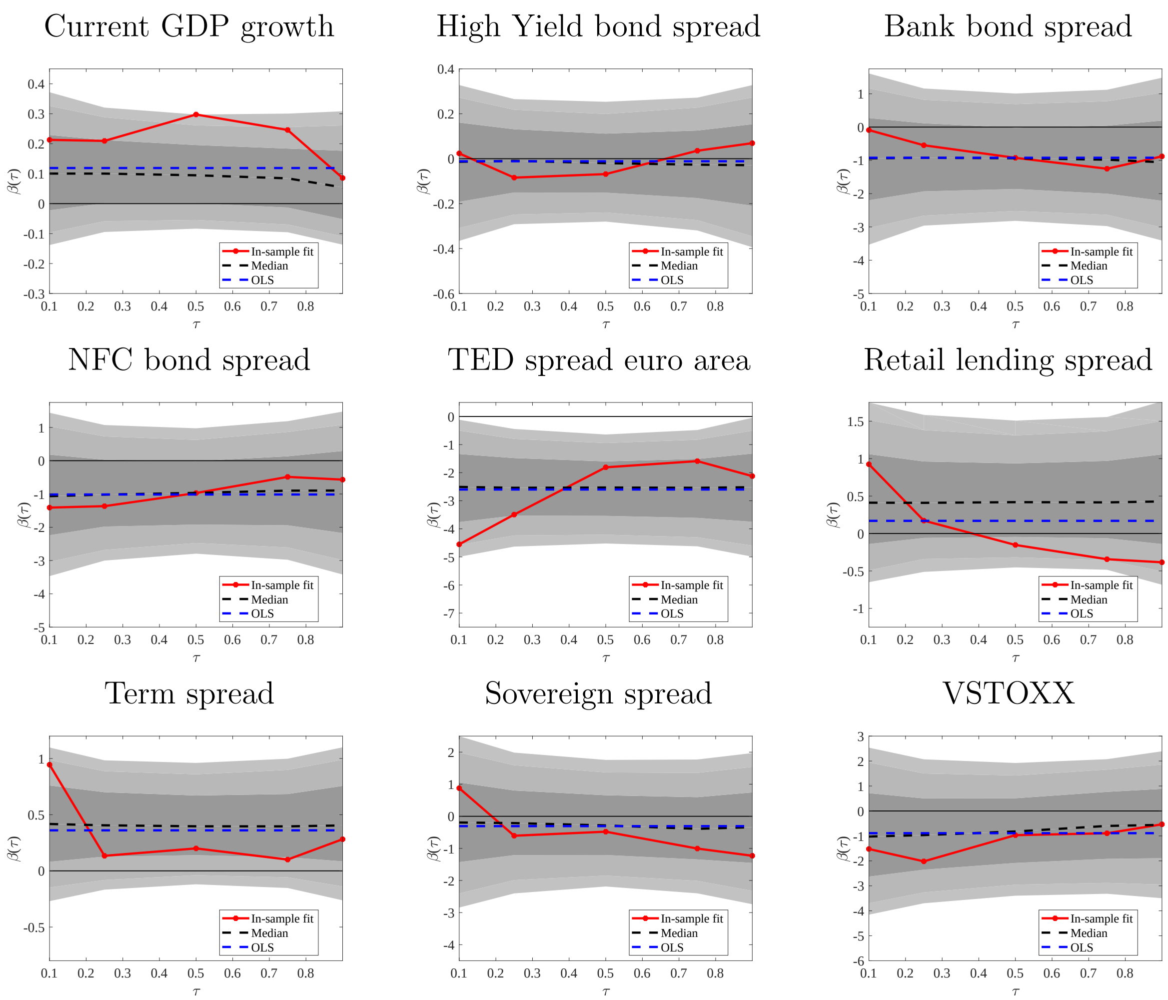


Figure A2: **Nonlinearity Tests: GDP.** Estimated coefficients corresponding to bivariate quantile regressions of one-year-ahead real GDP growth with current GDP growth and a measure of financial conditions as conditioning variables. Shaded regions indicate 68, 90 and 95 percent confidence bands under the null hypothesis of a linear data generating process: a VAR(4) containing GDP growth and a measure of financial conditions. Bands are obtained with bootstrap procedure with 5000 replications. For each financial variable we use the longest sample available. The sample for current GDP growth is 1986Q4-2018Q2.

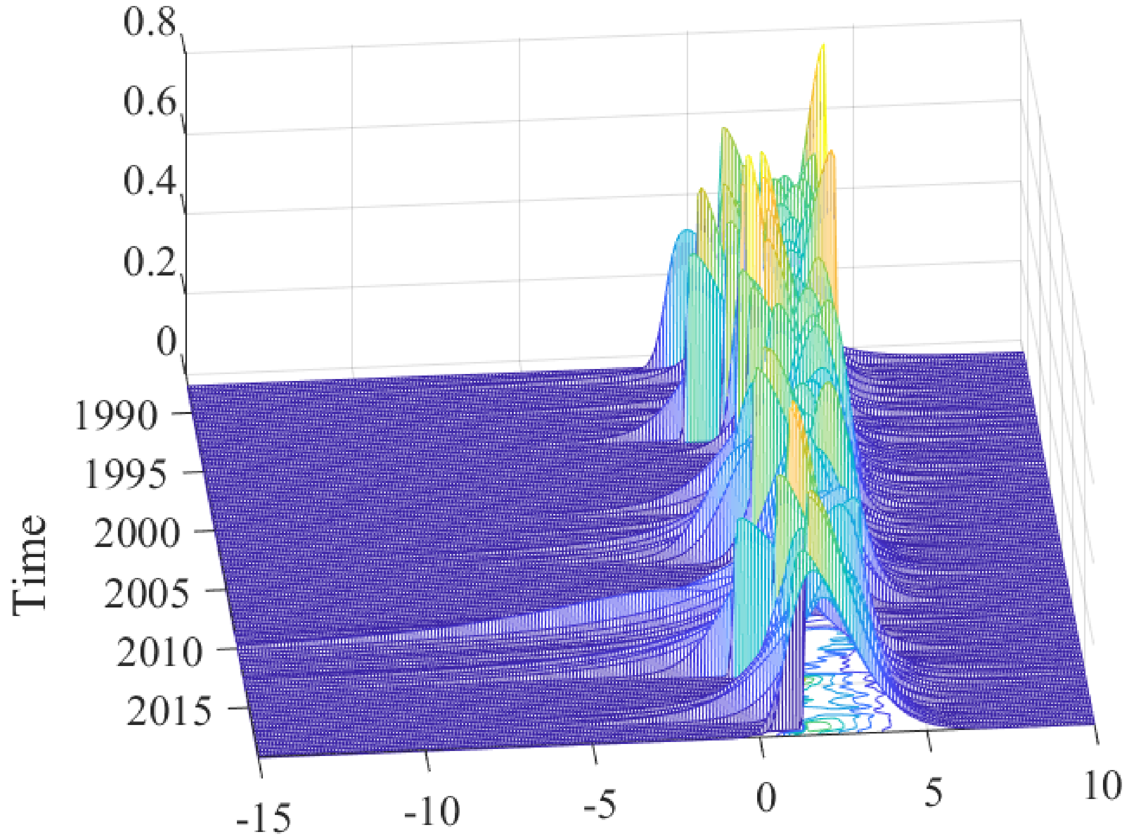


Figure A3: **Conditional Distribution of the GDP Growth Over Time.** Estimated one-year-ahead conditional distribution of real GDP growth based on bivariate quantile regressions with current GDP growth and CISS as conditioning variables over the sample 1986Q4-2018Q2.

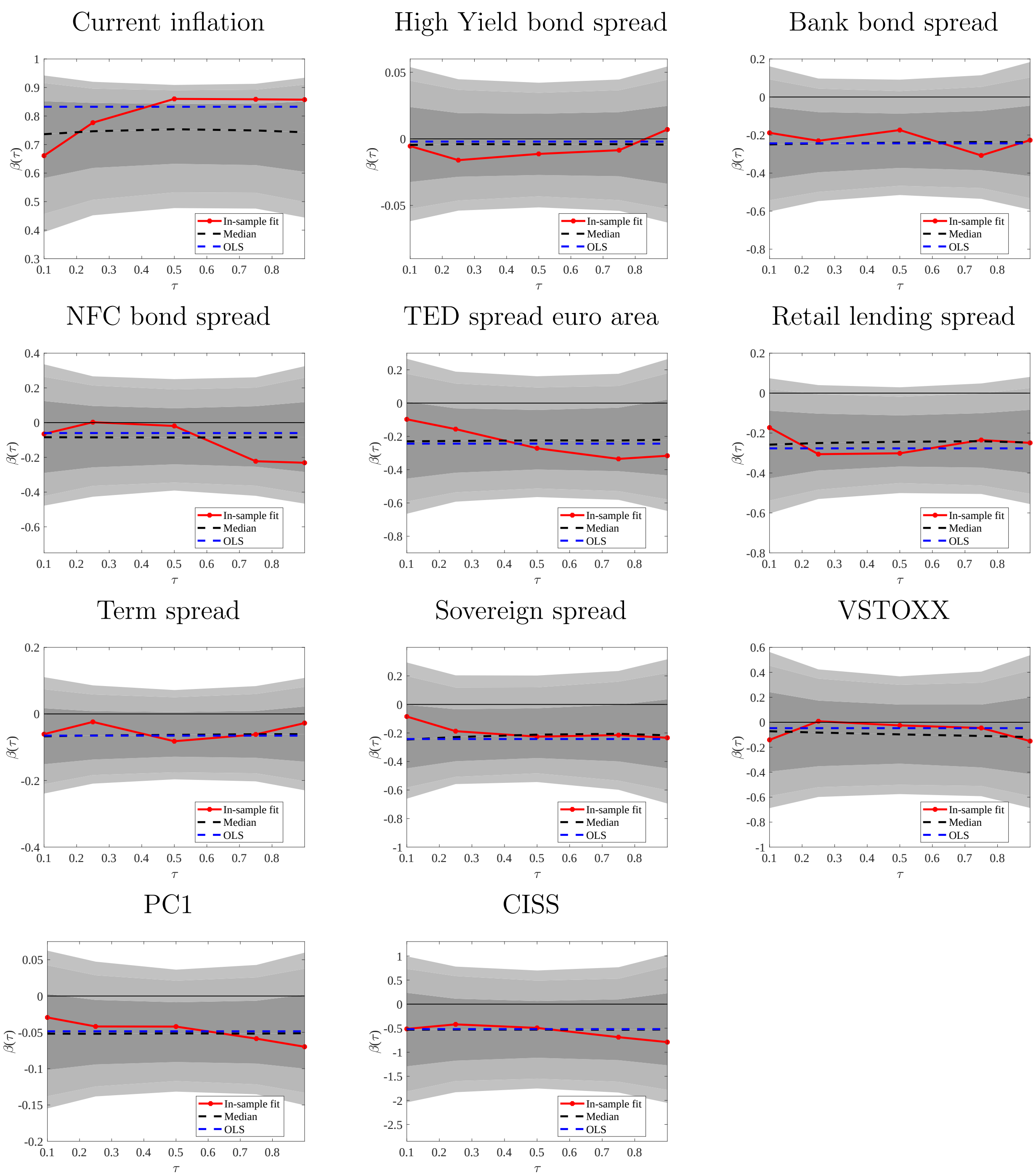


Figure A4: **Nonlinearity Test: Inflation.** Estimated coefficients corresponding to bivariate quantile regressions of one-year-ahead core inflation with current core inflation and a measure of financial conditions as conditioning variables. Shaded regions indicate 68, 90 and 95 percent confidence bands under the null hypothesis of a linear data generating process: a VAR(4) containing core inflation and a measure of financial conditions. Bands are obtained with bootstrap procedure with 5000 replications. For each financial variable we use the longest sample available. The sample for current inflation is 1986Q4-2018Q2.

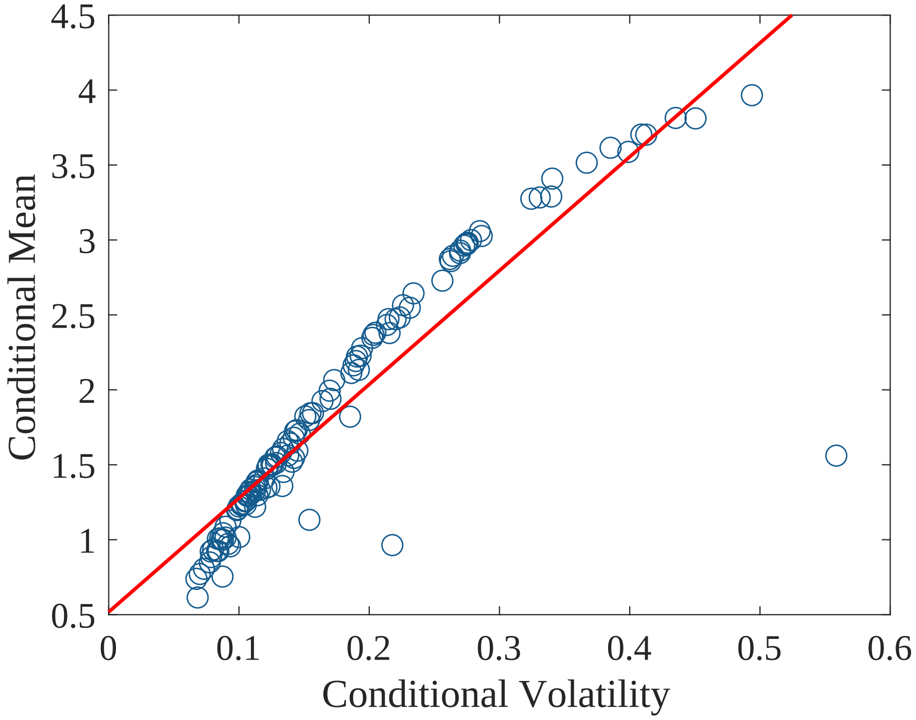
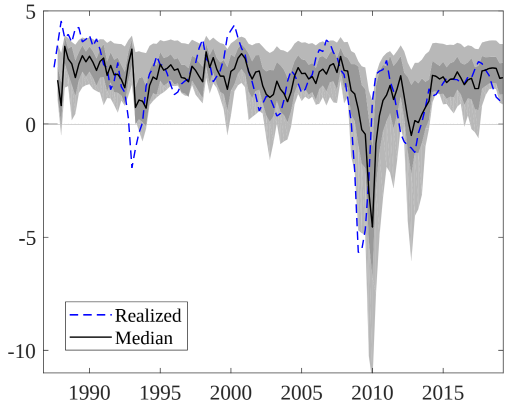
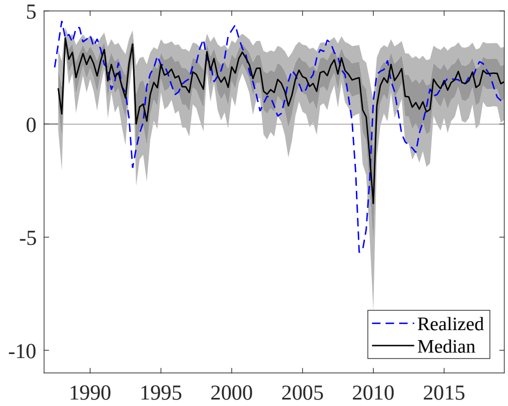


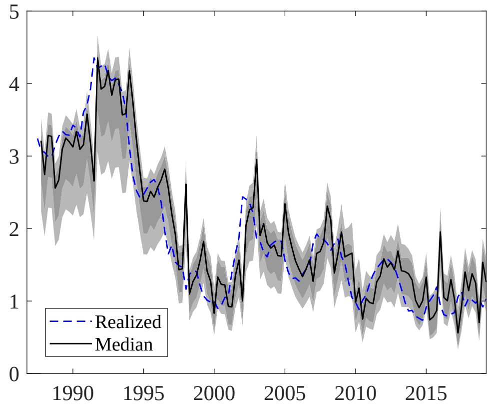
Figure A5: **Mean and Variance of the Conditional Distribution of Inflation.** Estimated conditional distribution of one-year-ahead core inflation based on bivariate quantile regressions with current core inflation and CISS as conditioning variables over the sample 1986Q4-2018Q2.



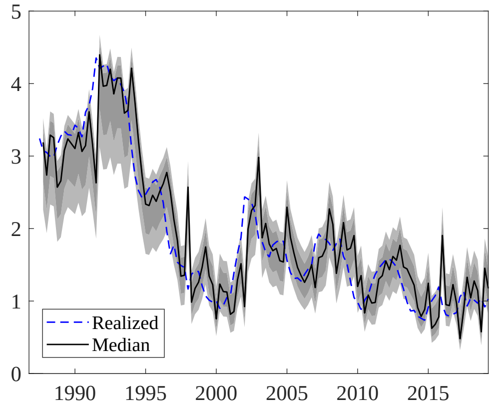
Output growth, with the CISS



Output growth, without the CISS



Inflation, with the CISS



Inflation, without the CISS

Figure A6: **Conditional Distributions of Real GDP Growth and Inflation Over Time - With and Without the CISS.** Estimated one-year-ahead conditional distribution of real GDP growth (top row) and Core inflation (bottom row) based on quantile regressions with the current value of the predicted variable (real GDP growth and inflation, respectively) with and without the CISS, over the sample 1986Q4-2018Q2.

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