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"WHAT CAUSES GLOBAL RECESSIONS? A QUANTILE REGRESSION APPROACH"

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ABSTRACT

The aim of this thesis is to examine the determinants of global recessions. In particular, we want to understand which variables are actually informative to explain what will happen to extreme negative realizations of world industrial production growth, by employing a quantile regression approach, as proposed by Adrian, Boyarchenko and Giannone (2019). As potential predictive variables, we consider indicators suggested by the financial literature and economic theory, such as financial uncertainty, credit market frictions, U.S. monetary policy stance, oil and commodity prices. Consistently with an extensive literature, our main finding is that the most important determinant is financial uncertainty, especially with reference to the Great Recession. Moreover, at the one-year-ahead horizon, our proxy of credit market frictions turns out to be quite informative. The Real Commodity Price Factor measure displays a strong first moment effect regarding the Great Recession, at the one-quarter-ahead horizon. Oil prices seem to be informative with reference to the 2009 global recession at the one-year-ahead horizon, consistently with the 2007-2008 oil price spike documented by Hamilton (2009) as an important factor contributing to the early stages of the Great Recession. Interestingly, the proxy variables for oil shocks considered do not prove to be informative for predicting global economic downturns. Regarding the U.S. monetary policy and Term Spread, quantile regression does not seem to add information with respect to a linear model.

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1. INTRODUCTION

The recent economic recession caused by the Covid-19 pandemic had some serious repercussions on many sectors and devastating effects on a global level. According to the World Bank, in 2020 the annual world Gross Domestic Product (GDP) growth hit the lowest value since 1961 (-3.1%[1]) and unemployment peaked at 6.9% of the labour force (International Labour Organization (ILO) global estimate)[2].

The Covid-19 global downturn was only the last episode of a historical series of global recessions[3] which had different causes. The 1982 global recession was caused by several developments, including the oil price shock of 1979 and a tightening of monetary policies in the United States (U.S.) and other advanced economies. In 1991, the heightened of geopolitical uncertainty and the sharp increase in oil prices associated to the 1990-1991 Gulf War, together with the widespread weakness of lending institutions in the U.S. contributed to the outbreak of a global recession. The 2009 global downturn followed the Great Financial Crisis, a period which was preceded by the loosening of regulation and supervision of financial markets and institutions, asset price and credit booms in a number of countries and the rapid expansion of high-risk lending, particularly in the U.S. mortgage markets. In September 2008, the collapse of Lehman Brothers triggered a full-scale financial and macroeconomic crisis. The high degree of interconnectedness between the U.S. and other financial markets caused the crisis to spread globally (Kose, Sugawara and Terrones, 2020). The magnitude of the negative effects of these phenomena on the world economy highlight the importance to identify some indicators to try to predict them. The debate in the literature is about macro versus financial determinants of the conditional distribution of GDP growth.

The aim of this thesis is to understand which variables are actually informative to explain what will happen to extreme negative realizations of world industrial production growth, relying on a quantile regression approach. Two samples are considered. The former ranges from June 1976 to December 2019, while the latter extends until December 2022, including the Covid-19 global

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[1] Data are available at: The World Bank (a), <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG>.
[2] Data are available at: The World Bank (b), <https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS>.
[3] Kose, Sugara and Terrones (2020) define a global recession as an annual contraction in global real GDP per capita along with a broad decline in various other measures of economic activity, including industrial production, trade, capital flows, oil consumption, and unemployment.

recession period. Different predictors, suggested by the literature and economic theory, are taken into consideration, in particular regarding financial uncertainty, U.S. monetary policy stance, oil and commodity prices.

From an econometric point of view, this thesis is related to the statistical literature on estimating and evaluating conditional distributions. In particular, we follow the approach of Adrian, Boyarchenko and Giannone (2019), who developed a two-step procedure for the estimation of the conditional probability distribution function. In the first step, they employ the quantile regressions of Koenker and Bassett (1978) to estimate the conditional quantile function. In the second step, they fit a parametric inverse cumulative distribution function with a known density function to the empirical conditional quantile function, for each quarter in their sample[4]. Since in our analysis we consider monthly data, we do this for each month in our samples. This procedure allows to transform the inverse cumulative distribution function from the quantile regression into a density function.

First, we investigate which variables display a significant relationship with the future world industrial production growth, at the one-quarter- and one-year- ahead horizons. Then, we consider the significant variables and, following Adrian, Boyarchenko and Giannone (2019), we test them for the presence of a non-linear relationship with future world industrial output growth. For those variables for which we reject the null hypothesis of the existence of a linear relationship, at the 95% confidence level, we investigate the left-tail behaviour of the conditional estimated skewed *t*-density functions for one-quarter- and one-year- ahead world industrial production growth, in the dates in which it hit the lowest values in correspondence of each global recession considered.

The main finding of this thesis regards volatility inside financial markets. Our proxy measure of financial uncertainty seems to be informative about the left-tail behaviour of the future world industrial production growth distribution, in particular with reference to the Great Recession. Increase in financial uncertainty coincide with a decline in the location and an increase in the scale of the distribution of future global GDP growth, thus with a leftward shift of the distribution, placing higher probability around particularly bad outcomes relative to good

[4] In their analysis, Adrian, Boyarchenko and Giannone (2019) consider quarterly data.

outcomes. This implies that adverse financial volatility shocks generate an increase in downside tail risk of future world industrial production growth. This result is important from a macroprudential perspective, highlighting the importance of monitoring the state of financial markets and is related to Caggiano and Castelnuovo (2023), who find evidence supporting the fact that the more global financial conditions deteriorate after a global financial uncertainty shock, the larger the world output contraction is. Moreover, employing a Vector Autoregressive (VAR) analysis, they find that the contraction in world output during the Great Recession would have been 13% lower in magnitude in absence of global financial uncertainty shocks.

In our analysis, the proxy measure of frictions in the credit markets seems to be informative at long horizons, but only considering the more limited sample. The results suggest that frictions inside the credit markets are not only first, but also second moment shocks, in particular regarding the 1991 and 2009 global recessions. Moreover, for what concerns the Great Recession, credit market frictions display also a third moment effect.

Concerning oil market dynamics, oil prices do not display substantial one-quarter-ahead predictive power while, with reference to the 2009 global recession, they show a first moment effect at the one-year-ahead horizon. This result proves to be consistent in both samples considered and could be related to the oil price increase in 2007-2008 documented by Hamilton (2009) as an important factor contributing to the early stages of the Great Recession. Strangely, oil prices do not display any predictive power for what concerns the 1982 global downturn, which is well known for being an oil-price-driven recession. Moreover, the oil shock measures considered do not seem to be informative to predict extreme negative outcomes of world industrial production growth. For what concerns other commodities, at the one-quarter-ahead horizon, the Real Commodity Price Factor displays a mean effect for what concerns the first 1982 global downturn and the 2009 global recession. This effect is particularly pronounced for the Great Recession.

With regard to the U.S. monetary policy and Term Spread, the quantile regression approach does not seem to add information with respect to a linear model.

By looking at downside risk measures, it seems that at short horizons the variables that predict the highest probability of observing extreme negative values of world industrial production growth are the Real Commodity Price Factor and VXO spliced for the first and the second downturn of the 1982 global recession, respectively; the Real Commodity Price Factor for the 1991 global recession; VXO spliced for the 2009 and Covid-19 global recessions. At long horizons, the variables that predict the highest probability of observing extreme left-tail realizations of the world industrial production growth distribution are Excess Bond Premium for the 1991 global recession, and WTI for the other global downturns considered.

The structure of the thesis is the following. Section 2 reviews the literature related to the conditional forecasting of global recessions and the more relevant predictive variables. Section 3 presents the data and empirical model employed in the analysis. Section 4 exposes the results obtained and Section 5 presents two summary measures of downside risk: downside entropy and expected shortfall. Section 6 concludes.

2. LITERATURE REVIEW

This thesis focuses on the examination of the drivers of the conditional distribution of future OECD+6NME industrial production (i.e., the industrial production of the member countries of the Organization for Economic Co-operation and Development and six non-member countries) growth, through the estimation of quantile regressions, with a particular focus on the left tail of the distribution. The drivers considered regard financial markets, U.S. monetary policy, oil and commodity prices.

As defined by The Conference Board (2022), from June 1976 to December 2022, the world economy has experienced four global recessions: in 1982, 1991, 2009 and 2020. The fact that cross-border trade and financial linkages have become stronger over the last decades has risen the odds of more pronounced and synchronous movements in the Global Business Cycle (Kose, Sugawara and Terrones, 2020).

With the aim of measuring downside risk, the International Monetary Fund (IMF, 2017) introduced the "Growth-at-Risk", a risk measure for GDP growth that indicates how severe a recession could become in an extreme situation where future GDP growth falls into the 5^{th} percentile of its probability distribution. In this thesis we consider OECD+6NME industrial production growth, which is a proxy of global GDP growth, as a Global Business Cycle indicator.

The Great Recession, which set off from the Global Financial Crisis, put emphasis on the role of financial markets in the business cycle analysis, giving rise to extensive literature about this topic. Adrian, Boyarchenko and Giannone (2019) study the future conditional distribution of GDP growth as a function of economic and financial conditions and highlight the fact that deteriorating financial conditions are associated with an increase in the conditional volatility and a decline in the conditional mean of GDP growth, leading the lower quantiles of GDP growth to vary with financial conditions and the upper quantiles to be stable over time. Their main finding is that downside risk to GDP growth is predicted by financial conditions, while upside risk is stable over time.

Kwark and Lee (2021) adopt the same methodology of Adrian, Boyarchenko and Giannone (2019), analysing the impact of the financial conditions on future GDP growth in Korea and find similar results: while the deterioration of financial conditions expands the downside risk of future GDP growth, its impact on the upside risk is insignificant.

Wang and Li (2021), using quantile regression and Bayesian-VAR models, demonstrate that deteriorating financial conditions and high systemic risk reinforce future downside risk when current GDP growth is relatively low in China.

Figueres and Jarociński (2020) examine which measures of financial conditions are informative about the tail risks to output growth in the euro area. They find that the ‘‘vulnerable growth’’ approach of Adrian, Boyarchenko and Giannone (2019) is relevant also for the euro area, using an appropriate indicator of financial conditions.

Giglio, Kelly and Pruitt (2016) use the quantile regression approach to evaluate the explanatory power of financial conditions and systemic risk to the conditional distribution of future real activity outcomes in the U.S. and Europe. They find that some measures of systemic risk are statistically significant predictors of the left tail of real activity outcomes.

Given the fact that credit markets are an important link in the propagation of economic uncertainty, Alessandri and Mumtaz (2019) estimate a non-linear VAR model, using monthly data covering the period between January 1973 and May 2014, to study how the response of the U.S. economy to uncertainty shocks depends on aggregate financial conditions. They find that uncertainty shocks have recessionary effects at all times, but their impact on output is six times larger when the economy is going through a financial crisis.

Caggiano, Castelnuovo and Groshenny (2014) investigate the impact of uncertainty shocks on unemployment during U.S. post-WWII recessionary episodes. They find evidence of non-linear dynamics for financial uncertainty, policy rate and inflation, observing an asymmetric evolution of the unemployment rate over the business cycle.

Moreover, Caggiano and Castelnuovo (2023) find some results on the importance of global financial uncertainty, indicating that financial stress following an increase in uncertainty might be an important factor contributing to the deterioration of global output and suggesting the existence of a global finance uncertainty multiplier.

Furthermore, Caldara, Scotti and Zhong (2023) investigate the drivers of uncertainty and tail risk of future GDP growth and corporate credit spreads using a Stochastic Volatility Vector Autoregression (SV-VAR). Considering macro and financial shocks in isolation, they show how shocks shape the conditional distribution of future economic conditions beyond the mean. They find that adverse macroeconomic and financial shocks lead to an increase in uncertainty and

downside tail risk concerning future GDP growth and corporate spreads, but only to a small reduction in upside tail risk.
Finally, Granziera and Sekhposyan (2019) evaluate the predictive abilities of a wide range of economic variables for the U.S. industrial production and inflation. They find that business cycle indicators, financial conditions, uncertainty and measures of past relative performances are generally useful for explaining the relative forecasting performances of a wide range of economic models of the Autoregressive Distributed Lag (ADL) type.

On the other end, Reichlin, Ricco and Hasenzagl (2020) evaluate the role of financial conditions as predictors of macroeconomic risk and find that there is limited value in financial variables for predicting recessions and, in general, for detecting GDP risk in advance. Moreover, from a macroprudential policy perspective, they argue the importance to monitor the joint dynamics of real and financial variables to detect accumulation of financial risk which may lead to crises in the future.
Furthermore, Plagborg-Møller et al. (2020), evaluating the potentially non-linear nexus between financial indicators and the distribution of future GDP growth, conclude that financial variables have very limited predictive power for the GDP growth distribution at short horizons (other than the mean), especially for what concerns the tail risk.
Ng and Wright (2013) emphasize the importance of the source of business cycle fluctuations. They suggest that recessions which originate in the financial markets are different from others, and that this could explain why some models and economic variables work well at some times whereas at other times their performances deteriorate.

Notable works highlight the effects of U.S. monetary policy on financial conditions. Using a medium-scale Bayesian VAR model, Miranda-Agrippino and Rey (2020) show that U.S. monetary policy is a driver of the Global Financial Cycle. They also document evidence consistent with the existence of a very powerful information effect of monetary policy that mostly impacted longer-term interest rates in the years after 2009.
Moreover, Miranda-Agrippino and Rey (2022) estimate a proxy VAR model which includes real economy as well as financial variables in order to understand their joint dynamics and find that following a U.S. monetary policy tightening, global financial conditions deteriorate materially.

For what concerns oil prices fluctuations, there are some important episodes to consider.
The Iranian Revolution beginning in November 1978, the Iran-Iraq War beginning in September 1980 and the First Persian Gulf War beginning in August 1990 were followed by a decrease in world oil production. Another important episode is the broad upswing in the price of oil beginning in 2004, that accelerated sharply in 2007, which differentiates from the aforementioned episodes for the fact that the price of oil rose abruptly in the absence of a significant physical disruption in the supply of oil (Hamilton, 2013).
Hamilton (2009) explores differences and similarities between the run-up of oil prices in 2007–2008 and earlier oil price shocks, looking at what caused these price increases and what effects they had on the economy. The principal cause of the 2007-2008 oil spike appears to have been the strong demand for oil from the emerging economies confronting the stagnating global production levels (see also Kilian and Hicks, 2013).
Although the causes were different, Hamilton (2009) also noted that what happened in the early stages of the 2007-2009 recession was quite consistent with the pattern observed in the recessions that followed earlier oil shocks and suggests that the oil price spike of 2007-2008 should be counted as an important factor contributing to the early stages of the Great Recession.
Jiménez-Rodríguez and Sánchez (2005) assess empirically the effects of oil price shocks on the real economic activity of the main industrialised OECD countries, focusing on the relationship between oil prices and GDP growth. They find evidence of non-linear effects of oil price on the real economic activity.
Finally, Engemann, Kliesen and Owyang (2011) found that oil prices are informative predictors of economic recessions in most of the countries they investigated.

3. DATA AND EMPIRICAL MODEL

3.1 Data

In this thesis we compare the results obtained running a quantile regression analysis on two samples, considering monthly observations. The first one ranges from June 1976 to December 2019, including three periods of global recession, more specifically in 1982, 1991, and 2009. We also replicate the analysis extending the dataset until December 2022, thus considering also the Covid-19 global recession, in order to investigate if the results remain consistent or change.

Our measure of global economic activity is the year-over-year OECD+6NME industrial production growth rate, which refers to the output of industrial establishments in different sectors worldwide, such as mining, manufacturing, electricity, gas, steam and air conditioning (OECD Data, 2023). The industrial production index for OECD countries and six major non-member economies (Brazil, China, India, Indonesia, the Russian Federation and South Africa) is reported in the OECD Main Economic Indicators (MEI) database from January 1958 until October 2011. To extend this dataset, Baumeister and Hamilton (2019) applied the same methodology employed by the OCED, using OECD industrial production and industrial production for the individual non-member countries (available in the MEI database). Finally, they applied the weights reported by the OECD (taken from the IMF's World Economic Outlook (WEO) database) to aggregate those series into a single index. From August 2018 onwards, they updated the index with the monthly weighted world industrial production growth rate of the Centraal Planbureau Netherlands Bureau for Economic Policy Analysis (CPB).

The year-over-year OECD+6NME industrial production growth rate is computed taking the logarithm difference between the value of the index in one month and its value one year before. This difference is then multiplied by 100, in order to express the measure in percentage terms.

3.1.1 Predictors

In this section we illustrate some measures that the literature and economic theory suggest being important to guide the Global Business Cycle. We considered them in our analysis to take into account the influence of aggregate demand shocks, aggregate supply shocks and financial shocks on future OECD+6NME industrial production[5] growth.

VXO spliced[6]. An indicator of uncertainty often employed in empirical studies is the Chicago Board Options Exchange Market Volatility Index (i.e., VIX index, also known as "fear index"), which measures the implied volatility of the S&P500 index options and represents a measure of market expectations of stock market volatility at time t over the next 30-day period, from 1986 onward. Following Bloom (2009), Andreasen et al. (2023) compute pre-1986 monthly returns volatilities through a backcasting procedure, by employing the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VIX index when they overlap from 1986 onward. In this way they obtained the VXO spliced, which in our analysis is taken into account as a measure of financial stress. To extend the dataset from April 2020 until August 2021, we consider the VXO values retrieved form the series available in the Federal Reserve Economic Data (FRED) database[7] and then, since this series was discontinued, for the remaining part of the sample the series is updated using the VIX[8] growth rate.

Effective Federal Funds Rate and Shadow Federal Funds Rate[9]. The Federal Funds Rate (i.e., the interest rate at which depository institutions trade Federal Funds with each other overnight) has been considered as the primary measure for the Federal Reserve's monetary policy stance. However, during the periods in which it hits the zero lower bound (in our time interval of interest: from January 2009 to November 2015 and from April 2020 to February 2022) it does not convey any information. For this reason, to summarize the effects of U.S. monetary policy we consider the Shadow Federal Funds Rate[10] (Wu and Xia, 2016), which controls for unconventional monetary policy, together with the Effective Federal Funds Rate[11] (i.e., the volume-weighted median of overnight Federal Funds transactions) for the part of sample in which the Shadow Rate is not available. Since Wu and Xia (2016) demonstrate that the Shadow

[5] Data are available at: Baumeister (2023), <https://sites.google.com/site/cjsbaumeister/datasets>.
[6] The VXO series has been spliced with S&P500 realized volatility as in Bloom (2009) and as updated by Andreasen et al. (2023).
[7] Data are available at: FRED (2021), <https://fred.stlouisfed.org/series/VXOCLS>.
[8] Data are available at: FRED (2023a), <https://fred.stlouisfed.org/series/VIXCLS>.
[9] Data are available at: Federal Reserve Bank of Atlanta (2022), <https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate>.
[10] The Shadow Rate was first introduced by Black (1995).
[11] Data are available at: FRED (2023b), <https://fred.stlouisfed.org/series/FEDFUNDS>.

Federal Funds Rate interacts with macro variables similarly as the Federal Funds Rate did historically, we put these two Federal Funds Rates in the same series.

WTI, Oil Supply Shocks, Oil Consumption Demand Shocks and Oil Inventory Demand Shocks. As a measure of oil prices, the "Spot Crude Oil Price: West Texas Intermediate" (WTI), from the FRED database[12], is considered. To investigate the effects of oil shocks on future global economic activity, measures of Oil Supply Shocks, Oil Consumption Demand Shocks and Oil Inventory Demand Shocks[13] (also known as "Speculative Oil Demand Shocks") obtained by Baumeister and Hamilton (2019) through a Bayesian description of the global oil market, are taken into account. In particular, the reasoning proposed by Baumeister and Hamilton (2019) refers to Kilian and Murphy (2014) who noted that an important factor in interpreting short-run comovements of quantities and prices of oil is the behaviour of inventories, observing that increased oil production in a specific month does not necessarily have to be consumed in that month but might instead go into inventories.

Real Commodity Price Factor. To take into account the commodity price dynamics, a measure suggested by Alquist, Bhattarai and Coibion (2020); Delle Chiaie, Ferrara and Giannone (2022), West and Wong (2014) is considered: the Real Commodity Price Factor (RCPF). This measure is related to business cycle fluctuations and relies on the common variation in a large cross-section of real commodity prices. The idea is that a factor extracted from this dataset captures the demand-driven global fluctuations that make all prices comove, while supply-side developments in specific commodity markets affect prices in idiosyncratic ways. The same 23 basic industrial and agricultural commodities (Aluminium; Barley; Beef; Coffee, Arabica; Coffee, Robusta; Copper, Cotton, A Index; Lead; Logs, Malaysian; Maize; Nickel; Palm Oil; Rice, Thai 5%; Rubber, SGP/MYS; Sawnwood, Malaysian; Soybeans; Soybean meal; Soybean oil; Sugar, U.S.; Sugar, world; Tin; Wheat, U.S. HRW; Zinc) considered by Baumeister, Korobilis and Lee (2022), which feed directly into the production of final goods and are thus related to real output, are used by Baumeister and Guérin (2021) to construct the RCPF series[14] considered in this thesis.

[12] Data are available at: FRED (2023c), <https://fred.stlouisfed.org/series/WTISPLC>.
[13] Data are available at: Baumeister (2023), <https://sites.google.com/site/cjsbaumeister/datasets>.
[14] Data are available at: Baumeister (2023), <https://sites.google.com/site/cjsbaumeister/datasets>.

Excess Bond Premium. As predictor we also consider a proxy measure of risks on financial markets, in particular those related to frictions in the credit markets: the Excess Bond Premium (EBP)[15]. Considering a sample of U.S. non-financial firms, Gilchrist and Zakrajšek (2012) build this measure following three major steps. First, they construct the so-called "GZ spread" for each bond on each day, which is given by the difference between the bond's yield-to-maturity implied by its daily price and the yield-to-maturity of a synthetic risk-free security that mimics exactly the cash flows of the corresponding corporate bond. Second, they construct a firm's default risk measure, which is needed to decompose each bond's "GZ spread" into two components: a component that captures the systematic movements in default risk of individual firms and a residual component, the EBP. For each publicly listed firm in their sample, they measure the default risk by the standard "Distance-to-Default" (DD) framework developed in Merton (1974). Third, they run a bond-level regression to decompose the bond's (log) credit spread into the expected default and the residual components. The estimated residual reflects a portion of the credit spread that is not attributable to the issuer's default risk. The EBP, obtained by averaging these residuals across issuers, captures fluctuations in the average price of bearing U.S. corporate credit risk, above and beyond the compensation for expected defaults. Given the importance of U.S. financial markets, we consider the EBP as a proxy of frictions in the global financial markets. We acknowledge the existence of EBP measures for euro area countries (see Gilchrist and Mojon, 2016), but we do not consider them because of data limitations.

U.S. Term Spread. The 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity series from the FRED database[16], calculated as the spread between 10-Year U.S. Treasury bond yield and 2-Year U.S. Treasury bond yield, is considered to capture agents' expectations about the U.S. government solvency.

3.2 Preliminary analysis

We want to assess which shocks guide the Global Business Cycle, more specifically those that potentially have the stronger impact on the left tail of the OECD+6NME industrial production growth distribution, causing global recessions.

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[15] Data are available at: Board of Governors of the Federal Reserve System (2016), <https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html>.

[16] Data are available at: FRED (2023d), <https://fred.stlouisfed.org/series/T10Y2YM>.

In particular, we want to see which among a set of selected variables help to predict the OECD+6NME industrial production growth. To do this, we run two Ordinary Least Squares (OLS) forecasting regressions on each predictor at time t, considering the year-over-year OECD+6NME industrial production growth rate at time $t + 3$ (one quarter ahead) and $t + 12$ (one year ahead) as dependent variables, to assess which predictors have mean effects on the distribution at these two horizons, according to the following equation:

$$y_{t+i} = \beta_0 + \beta_1 x_t + e_{t+i} \ ,$$

where $i = 3, 12$, depending on the forecast horizon considered, y_{t+i} is the future OECD+6NME industrial production growth rate, x_t is the predictor considered, β_0 is the intercept, β_1 is the slope coefficient that we want to estimate and e_{t+i} is the error term.

We run these regressions on two samples that start in June 1976. The former stops in December 2019, while the latter includes the Covid-19 global recession period, ending in December 2022.

Referring to the first sample, *Table 1* reports the estimated coefficients associated with each OECD+6NME industrial production growth indicator considered. At the one-quarter-ahead horizon (Column 1), VXO spliced (-0.15003, p-value: 3.7882 x 10^{-17}), WTI (-0.012855, p-value: 0.012288), Oil Supply Shocks (-0.18407, p-value: 0.05958), RCPF (2.1495, p-value: 8.2335 x 10^{-12}) and EBP (-3.5594, p-value: 3.3262 x 10^{-58}) show a significant relationship with the OECD+6NME industrial production growth. While, at the one-year-ahead horizon (Column 2) the variables which present significant coefficients are the Effective Federal Funds Rate together with the Wu-Xia Shadow Federal Funds Rate (-0.082807, p-value: 0.0072919), WTI (-0.038638, p-value: 8.8787 x 10^{-15}), RCPF (1.7023, p-value: 7.0783 x 10^{-8}), EBP (-1.3938, p-value: 1.1065 x 10^{-8}) and the U.S. Term Spread (0.50305, p-value: 0.00091408).

Table 1. OLS forecasting regression estimated coefficients - First sample: June 1976 – December 2019

	(1)	(2)
Variables	OECD + 6NME IP GR_{t+3}	OECD + 6NME IP GR_{t+12}
VXO $spliced_t$	**-0.15003*** **	-0.026976
	(0.017205)	(0.018305)
EFFR + $SFFR_t$	0.008997	**-0.082807*** **
	(0.031092)	(0.030737)
WTI_t	**-0.012855** **	**-0.038638*** **
	(0.0051162)	(0.0048338)
OSS_t	**-0.18407* **	0.017827
	(0.097494)	(0.098173)
$OCDS_t$	0.031858	0.049543
	(0.039415)	(0.039532)
$OIDS_t$	0.13975	-0.089917
	(0.12741)	(0.12731)
$RCPF_t$	**2.1495*** **	**1.7023*** **
	(0.3073)	(0.31121)
EBP_t	**-3.5594*** **	**-1.3938*** **
	(0.19421)	(0.23992)
$T10Y2YM_t$	-0.18498	**0.50305*** **
	(0.15237)	(0.15082)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Table 2. OLS forecasting regression estimated coefficients - Second sample: June 1976 – December 2022

Variables	(1) OECD + 6NME IP GR_{t+3}	(2) OECD + 6NME IP GR_{t+12}
VXO $spliced_t$	**-0.1499*****	0.0099192
	(0.018025)	(0.019037)
EFFR + $SFFR_t$	0.0047134	**-0.082456****
	(0.032726)	(0.032557)
WTI_t	**-0.0097242***	**-0.042088*****
	(0.0053197)	(0.0052111)
OSS_t	**-0.20492****	-0.040032
	(0.098132)	(0.098499)
$OCDS_t$	**0.087519****	0.020405
	(0.039601)	(0.04)
$OIDS_t$	0.04934	0.011116
	(0.1344)	(0.13511)
$RCPF_t$	**2.1942*****	**1.6972*****
	(0.31774)	(0.33185)
EBP_t	**-3.6295*****	**-1.235*****
	(0.21546)	(0.25925)
$T10Y2YM_t$	-0.024387	**0.58581*****
	(0.16448)	(0.16304)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Table 2 reports the estimated coefficients obtained running the OLS forecasting regressions on the second sample. In Column 1, VXO spliced (-0.1499, p-value: 7.0926 x 10^{-16}), WTI (-0.0097242, p-value: 0.068094), Oil Supply Shocks (-0.20492, p-value: 0.037239), Oil Consumption Demand Shocks (0.087519, p-value: 0.027513), RCPF (2.1942, p-value:

1.3748 x 10^{-11}) and EBP (-3.6295, p-value: 1.0253 x 10^{-51}) show a significant relationship with the OECD+6NME industrial production growth one quarter ahead. While, at the one-year-ahead horizon (Column 2) the variables which present significant coefficients are the Effective Federal Funds Rate together with the Wu-Xia Shadow Federal Funds Rate (-0.082456, p-value: 0.011599), WTI (-0.042088, p-value: 4.2989 x 10^{-15}), RCPF (1.6972, p-value: 4.3675 x 10^{-7}), EBP (-1.235, p-value: 2.4393 x 10^{-6}) and the U.S. Term Spread (0.58581, p-value: 0.00035638).

For both samples, as expected, the relationships expressed by the significant coefficients indicate that when there is an increase in financial uncertainty, oil prices and frictions in the credit markets, future OECD+6NME industrial production growth decrease. The same is true also when there is a monetary policy tightening or an oil supply shock. While, when there is a positive oil consumption demand shock (only considering the Covid-19 global recession in the sample), this has a positive effect on the future OECD+6NME industrial production growth. On the other hand, counterintuitive are the positive coefficient estimates obtained for the RCPF and U.S. Term Spread. Regarding the RCPF result, it could be due to the characteristics of the indicator, since it captures the demand-driven global fluctuations that make the commodity prices comove. For what concerns the positive relationship between the U.S. Term Spread and the one-year-ahead OECD+6NME industrial production growth, it could be related to the fact that an increase in the slope of the 10-year yield curve implies positive expectations of future growth, which can be interpreted as an indicator of future expansion.

Interestingly WTI coefficients, which result significant at both horizons in both samples, indicate stronger effects of oil prices fluctuations at longer horizons. On the other hand, the RCPF and EBP significant coefficients show stronger effects at the one-quarter-ahead horizon.

In terms of magnitude, the coefficient estimates for each significant predictor remain quite consistent between the two samples, with some differences in terms of significance. Notably, the Oil Consumption Demand Shocks measure results significant only considering the sample which includes the Covid-19 global recession.

Particularly interesting appears the fact that the Federal Funds Rates variable turns out to be significant only at the one-year-ahead horizon and not at the one-quarter-ahead horizon, in both samples. This result clearly indicates the lags in the U.S. monetary policy transmission, that is affected by the functioning of the money market.

We are interested in studying how shocks shape the conditional distribution of future OECD+6NME industrial production growth beyond the mean, focusing on left-tail risk. To do this, we analyse which significant predictors move the left tail of the distribution, by means of a quantile regression analysis, following the approach explained in the next paragraph.

3.3 Quantile regression approach

Quantile regression is a flexible tool for investigating the impact of different shocks on the left tail of the OECD+6NME industrial production growth, as opposed to focus on the central tendency via least squares. Following the conditional forecasting approach of Adrian, Boyarchenko and Giannone (2019), we rely on quantile regressions to characterize formally the conditional relationship between future OECD+6NME industrial production growth and each significant predictor. We investigate each predictor individually, asking whether or not they provide significant information about the future behaviour of OECD+6NME industrial production growth.

Let us denote by y_{t+h} the average year-over-year growth rate of OECD+6NME industrial production between t and $t+h$ and by x_t a vector containing the conditioning variables, including a constant. In a quantile regression of y_{t+h} on x_t the regression slope β_τ is chosen to minimize the quantile weighted absolute value of errors:

$$\widehat{\beta_\tau} = \arg\min_{\beta_\tau \in \mathbb{R}^k} \sum_{t=1}^{T-h} (\tau \cdot \mathbf{1}_{(y_{t+h} \geq x_t \beta)} \, |y_{t+h} - x_t \beta_\tau| + (1-\tau) \cdot \mathbf{1}_{(y_{t+h} < x_t \beta)} \, |y_{t+h} - x_t \beta_\tau|)$$

(1),

where $\mathbf{1}_{(\cdot)}$ denotes the indicator function and τ denotes the collection of quantiles[17]. Equation (1) highlights two main differences between quantile and OLS regressions. First, while the OLS regression minimizes the sum of squared errors, the quantile regression minimizes the sum of absolute errors. Second, quantile regression puts different weights on the errors depending on whether an error term is above or below the quantile (Adrian, Boyarchenko and Giannone, 2019). The predicted value from the regression expressed by equation (1) is the quantile of y_{t+h} conditional on x_t,

$$\widehat{Q_{y_{t+h}|x_t}}(\tau|x_t) = x_t\widehat{\beta_\tau} \quad (2),$$

which Koenker and Bassett (1978) show is a consistent linear estimator of the quantile function of y_{t+h} conditional on x_t.

The quantile regression (2) provides approximate estimates of the quantile function, which is an inverse cumulative distribution function.

3.3.1 Skewed *t*-distribution

Since the estimates provided by equation (2) are difficult to map into a probability distribution function because of approximation error and estimation noise, following Adrian, Boyarchenko and Giannone (2019), we fit the skewed *t*-distribution developed by Azzalini and Capitanio (2003) in order to smooth the quantile function and recover a probability density function:

$$f(y;\, \mu,\sigma,\alpha,v) = \frac{2}{\sigma}\, t\left(\frac{y-\mu}{\sigma}; v\right) T\left(\alpha\, \frac{y-\mu}{\sigma} \sqrt{\frac{v+1}{v+\left(\frac{y-\mu}{\sigma}\right)^2}}; v+1\right) \quad (3),$$

where $t(\cdot)$ and $T(\cdot)$ denote the Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of the Student *t*-distribution, respectively.

The four parameters of the distribution set the location μ, scale σ, fatness v, and shape α. Relative to the *t*-distribution, the skewed *t*-distribution adds the shape parameter which regulates the skewing effect of the CDF on the PDF. The intuition for the derivation is that a base probability distribution, in this case $t\left(\frac{y-\mu}{\sigma}; v\right)$, gets shaped by its cumulative distribution function, and rescaled by a shape parameter α. The notable special case, when $\alpha = 0$, is the traditional *t*-distribution. In the case of both $\alpha = 0$ and $\nu = \infty$, the distribution reduces to a

[17] $\tau = \{0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95\}$

Gaussian with mean μ and standard deviation σ. When $\nu = \infty$ and $\alpha \neq 0$, the distribution is a skewed normal (Adrian, Boyarchenko and Giannone, 2019).

For each month, we choose the four parameters $\{\mu_t, \sigma_t, \alpha_t, v_t\}$ of the skewed *t*-distribution f to minimize the squared distance between the estimated quantile function $Q_{y_{t+h}|x_t}(\tau)$ from (2) and the quantile function of the skewed *t*-distribution $F^{-1}(\tau\,;\,\mu_t, \sigma_t, \alpha_t, \nu_t)$ from (3) to match the 5, 25, 75, and 95 percent quantiles:

$$\{\widehat{\mu_{t+h}}, \widehat{\sigma_{t+h}}, \widehat{\alpha_{t+h}}, \widehat{v_{t+h}}\} = \arg\min_{\mu,\sigma,\alpha,v} \sum\nolimits_{\tau} (\widehat{Q_{y_{t+h}|x_t}}(\tau|x_t) - F^{-1}(\tau\,;\,\mu, \sigma, \alpha, \nu))^2 \,,$$

where $\widehat{\mu_{t+h}} \in \mathbb{R}$, $\widehat{\sigma_{t+h}} \in \mathbb{R}^+$, $\widehat{\alpha_{t+h}} \in \mathbb{R}$, $\widehat{v_{t+h}} \in \mathbb{Z}^+$ are functions of the conditioning variables x_t[18].

This can be intended as an exactly identified non-linear cross-sectional regression of the predicted quantiles on the quantiles of the skewed *t*-distribution (Adrian, Boyarchenko and Giannone, 2019).

[18] We drop the explicit dependence for notation convenience.

4. EMPIRICAL RESULTS

In this chapter we present the results obtained by employing the quantile regression approach considering the predictors which resulted significant in the preliminary analysis, distinguishing between our two samples of interest.

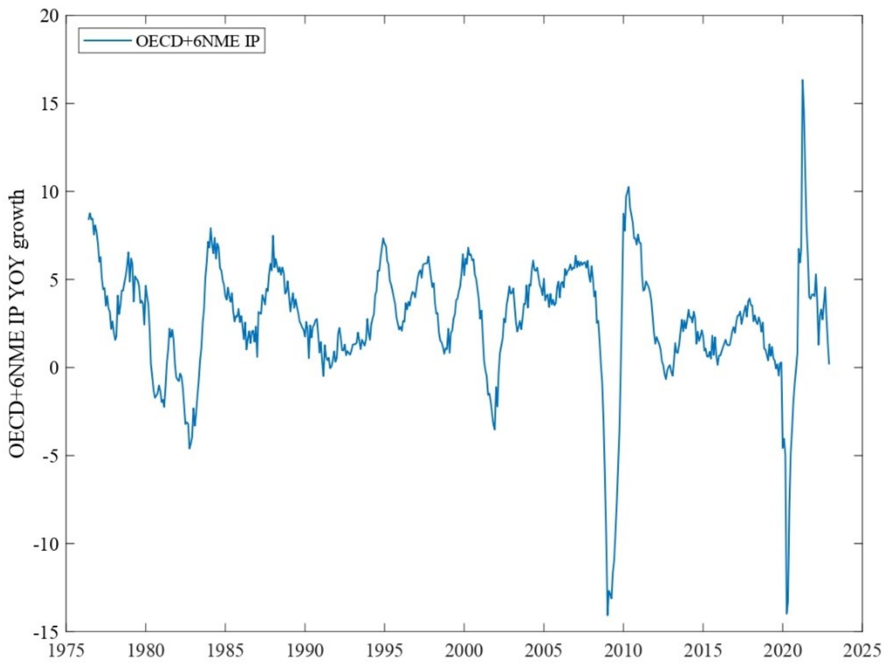
For each predictor, we plot the 68%, 90% and 95% confidence bands for the null hypothesis that the true data-generating process is a flexible and general linear model for growth and the predictor considered, to see if the quantile regression analysis actually adds information which a linear model does not provide. Following Adrian, Boyarchenko and Giannone (2019), confidence bands are computed, under the hypothesis of constant slopes, using the distribution of coefficients estimated in 1000 bootstrapped samples generated employing a VAR model with twelve lags (since we are considering monthly data), Gaussian errors and a constant, fitted to the full-sample evolution of the predictor and OECD+6NME industrial production growth. Quantile coefficient estimates that fall outside the confidence bands indicate that the relation between OECD+6NME industrial production growth and the predictive variable is non-linear. We consider a 5% significance level reference threshold.

For those predictors which show significant quantile regression coefficients, we plot two versions of the fitted conditional probability density functions of OECD+6NME industrial production growth at time $t + h$ (where $h = 3, 12$): one conditional on both OECD+6NME industrial production growth and the predictor considered, and one conditional only on OECD+6NME industrial production growth. The conditioning variables are considered at time t. We do this for specific dates, referring to the periods of global recession.

More specifically, relying on the OECD+6NME industrial production growth time series (*Figure 1*), we select the "trough" dates of each global recession, as the points in time we want to forecast (i.e., $t + h$), to show the predictive power of each significant predictor for what concerns the worst states of the Global Business Cycle, one quarter and one year ahead. Since the 1982 global recession can be divided in two phases, we consider two dates: March 1981 for the first downturn and October 1982 for the second one. For what concerns the 1991 global recession, the date considered is March 1991, while January 2009 is the forecast date for the

Great Recession. In the second sample, we also take into account April 2020 as the "trough" date of the Covid-19 global recession.

Figure 1. Monthly year-over-year OECD+6NME industrial production growth rate time series[19]



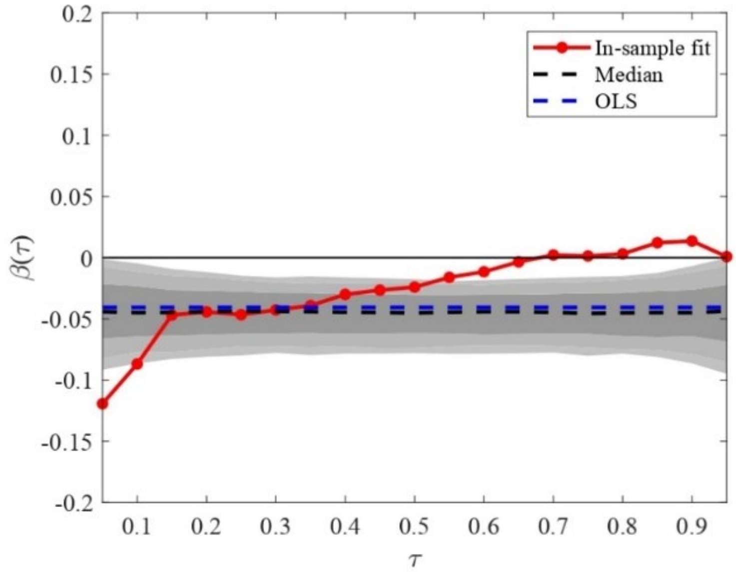
4.1 VXO spliced

From the preliminary analysis, our measure of financial stress results significant one quarter ahead. Accordingly, *Figure 2* shows the estimated coefficients in quantile regressions of one-quarter-ahead OECD+6NME industrial production growth on VXO spliced. For both samples, the estimated coefficients are significantly different, at the 5% level, from the OLS coefficients, at both the lower and the upper quantiles. Our focus is on the significance in the left tail.

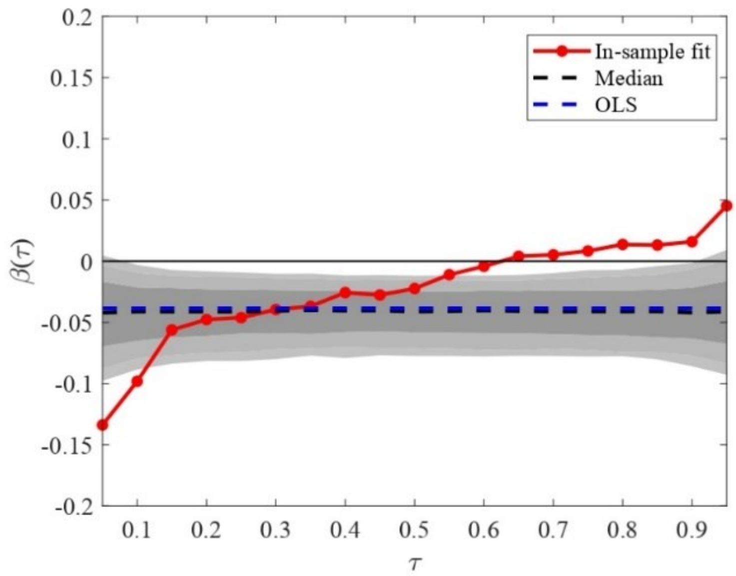
[19] Source: own elaboration on data from Baumeister (2023), <https://sites.google.com/site/cjsbaumeister/datasets>.

Figure 2. One-quarter-ahead estimated quantile coefficients: VXO spliced

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



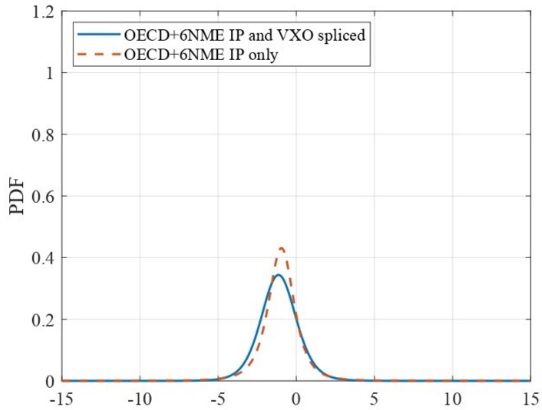
To analyse more in depth the predictive behaviour of VXO spliced, the panels in *Figures 3* and *4* show the estimated skewed *t*-density functions for one-quarter-ahead OECD+6NME industrial production growth, with the density estimated conditional on current OECD+6NME industrial production growth and VXO spliced, in the selected dates. For comparison, we also report the skewed *t*-density functions obtained by conditioning on current OECD+6NME industrial production growth only.

Figure 3. One-quarter-ahead probability densities: VXO spliced – first sample

1982 global recession

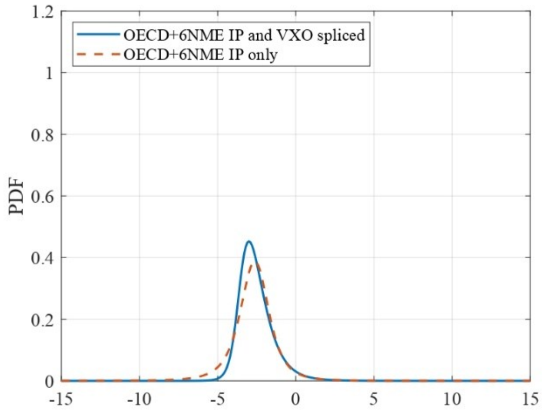
Phase 1

Panel A: $t + 3$ = March 1981 (trough)



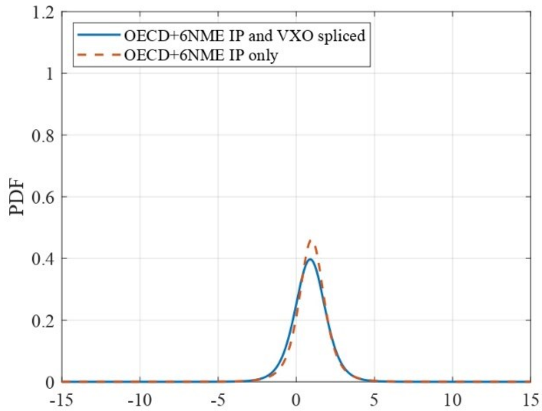
Phase 2

Panel B: $t + 3$ = October 1982 (trough)



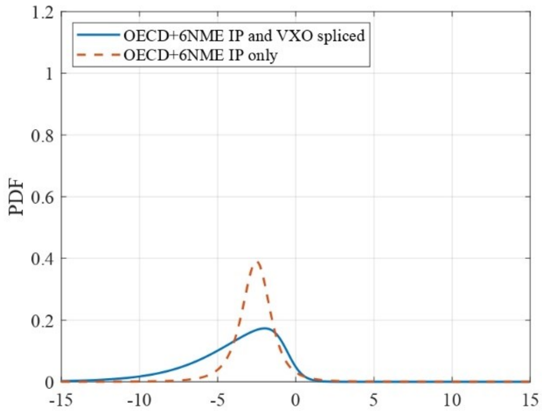
1991 global recession

Panel C: $t + 3$ = March 1991 (trough)



Great Recession

Panel D: $t + 3$ = January 2009 (trough)



Referring to the first sample, in *Figure 3*, **Panel D** the distribution conditional on both OECD+6NME industrial production growth and VXO spliced displays lower mean and higher variance that the distribution conditional on OECD+6NME industrial production growth only. Moreover, the double-conditioned distribution is also negatively skewed, showing expanded downside risks with respect to the distribution conditional only on OECD+6NME industrial production growth. This evidence for the Great Recession, which set off from the Global Financial Crisis, suggests that financial shocks are not only first moment, but also second and third moment shocks, since an increase in financial stress lowers the mean, expands the variance of the future OECD+6NME industrial production growth distribution, and even skews it to the left. For what concerns the 1982 and 1991 global downturn dates considered, the behaviour of the two conditional distributions is similar, with the double-conditioned distribution showing a slightly lower mean with respect to the single-conditioned one in **Panels A** and **B**.

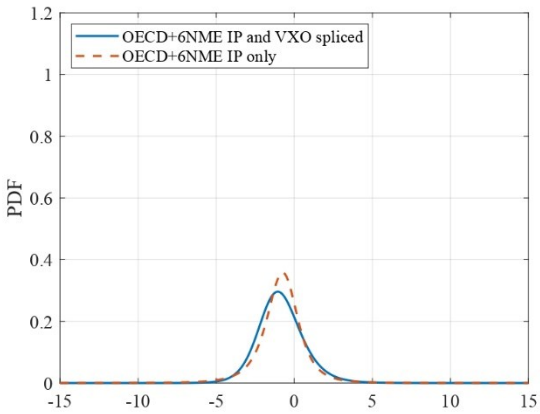
Figure 4 shows the results obtained considering also the Covid-19 global recession in the sample. Notably, in **Panel D** the distribution conditional on both OECD+6NME industrial production growth and VXO spliced shows slightly lower mean and higher variance than the distribution conditional on OECD+6NME industrial production growth only but, differently from the results obtained previously, the double-conditioned distribution is quite symmetric. This evidence for the Great Recession, considering the extended sample, suggests that financial shocks are substantially second moment shocks, since the strongest effect of an increase in financial stress is the expansion of the variance of the distribution. Moreover, in **Panels A** and **C** the distribution conditional on both OECD+6NME industrial production growth and VXO spliced displays slightly lower mean and higher variance with respect to the one conditional only on OECD+6NME industrial production growth. For what concerns the second "trough" date of the 1982 global recession (**Panel B**) and the one referring to the Covid-19 global downturn (**Panel E**), the double-conditioned distribution shows a slightly lower mean with respect to the single-conditioned one, a similar behaviour in the right tail but thinner (null) left tails.

Figure 4. One-quarter-ahead probability densities: VXO spliced - second sample

1982 global recession

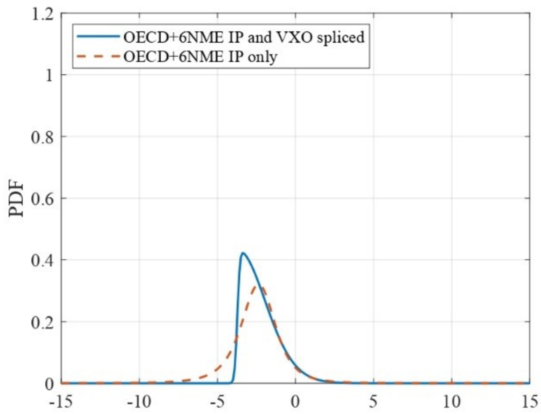
Phase 1

Panel A: $t + 3$ = March 1981 (trough)



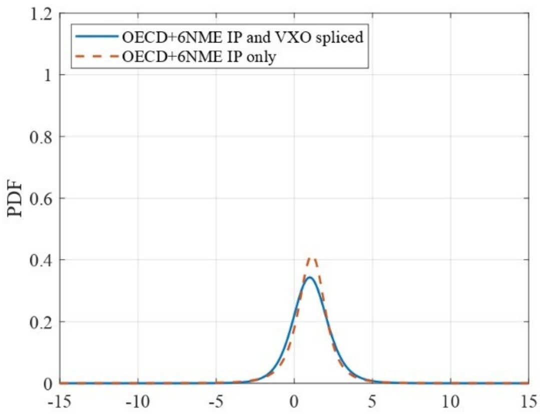
Phase 2

Panel B: $t + 3$ = October 1982 (trough)



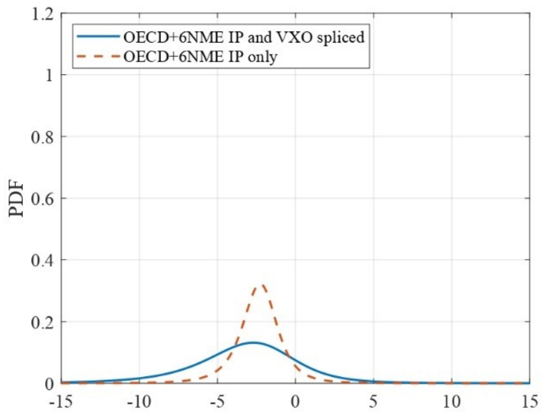
1991 global recession

Panel C: $t + 3$ = March 1991 (trough)



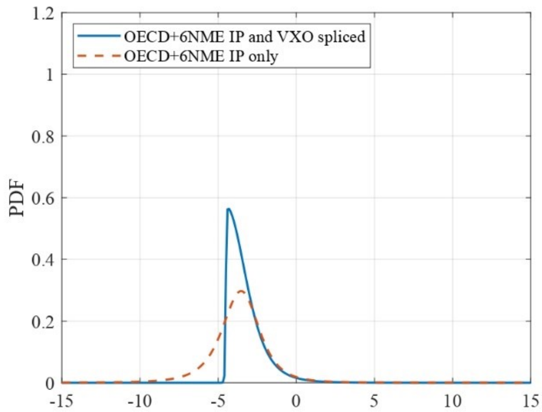
Great Recession

Panel D: $t + 3$ = January 2009 (trough)



Covid-19 global recession

Panel E: $t + 3$ = April 2020 (trough)

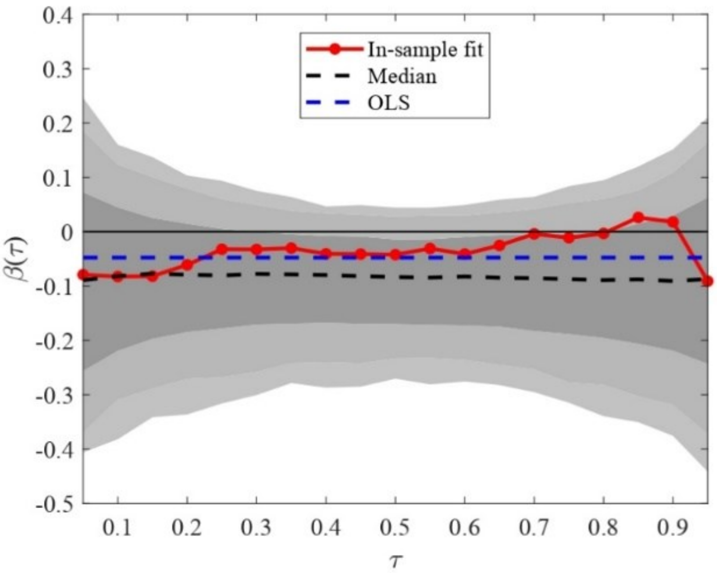


4.2 Effective Federal Funds Rate and Shadow Federal Funds Rate

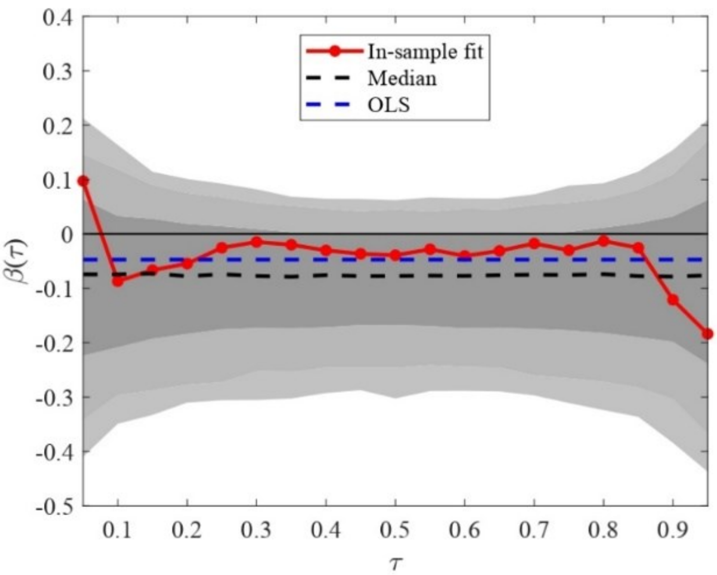
In the preliminary simple forecasting regressions, the Federal Funds Rate coefficients resulted significant at the one-year-ahead horizon. *Figure 5* shows the estimated coefficients in quantile regressions of one-year-ahead OECD+6NME industrial production growth on the Federal Funds Rates. Regarding both samples, the estimated coefficients are not significantly different from those obtained by an OLS regression. This suggests that, considering a quantile regression, the Effective Federal Funds Rate and the Shadow Federal Funds Rate are uninformative for predicting tail outcomes, for the time periods considered in our analysis.

Figure 5. One-year-ahead estimated quantile coefficients: EFFR+SFFR

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

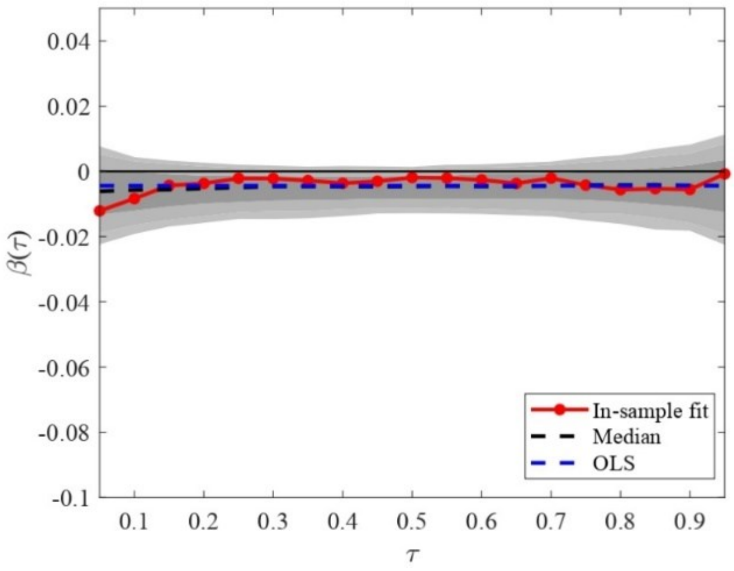


4.3 WTI

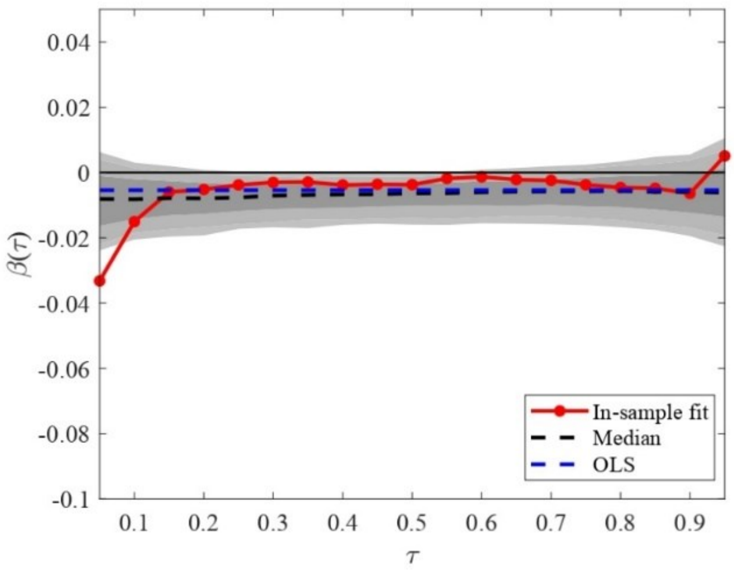
For what concerns oil prices, in accordance with the preliminary analysis results, in *Figure 6* we show the estimated coefficients in quantile regressions of one-quarter-ahead OECD+6NME industrial production growth on WTI. While, considering the first sample the non-linear relationship between future OECD+6NME industrial production growth and WTI is muted, when we include the Covid-19 global recession in the sample, the estimated quantile regression coefficient at the 5^{th} quantile results significantly different, at the 5% level, from the linear coefficients.

Figure 6. One-quarter-ahead estimated quantile coefficients: WTI

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



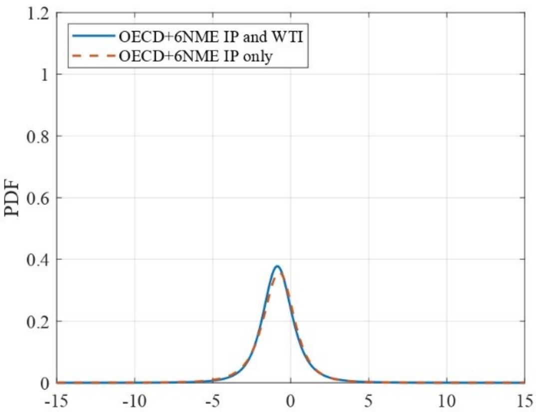
Considering the second sample, the panels in *Figure 7* show the estimated PDFs for one-quarter-ahead OECD+6NME industrial production growth, with the density estimated conditional on current OECD+6NME industrial production growth and WTI, in the selected dates. For comparison, we also plot the PDFs conditional on current OECD+6NME industrial production growth only. In all panels, the two distributions do not display a substantial different behaviour, suggesting that WTI does not help to predict one-quarter-ahead growth, in all the selected dates.

Figure 7. One-quarter-ahead probability densities: WTI - second sample

1982 global recession

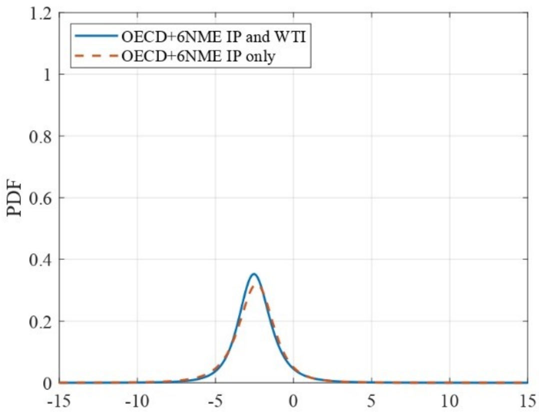
Phase 1

Panel A: $t + 3$ = March 1981 (trough)



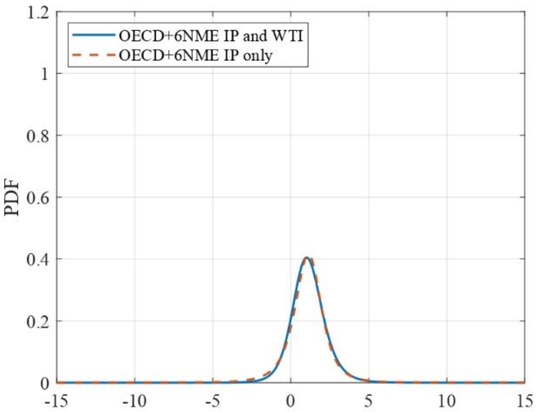
Phase 2

Panel B: $t + 3$ = October 1982 (trough)



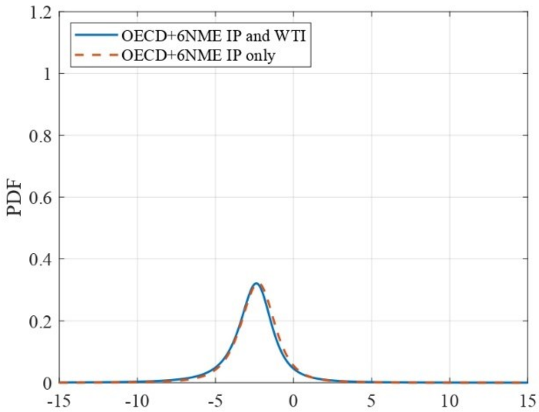
1991 global recession

Panel C: $t + 3$ = March 1991 (trough)



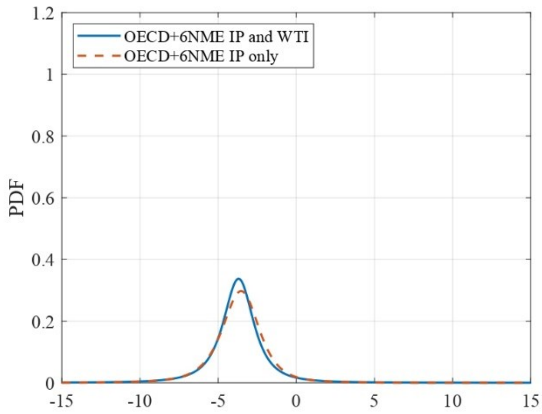
Great Recession

Panel D: $t + 3$ = January 2009 (trough)



Covid-19 global recession

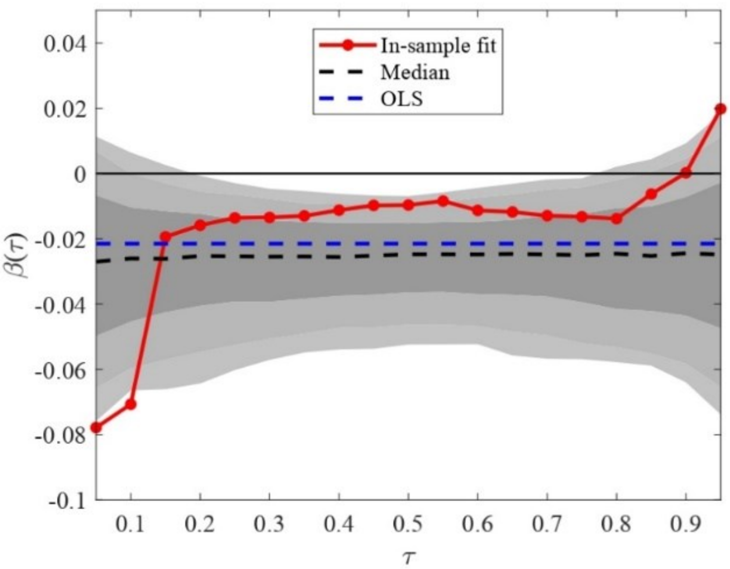
Panel E: $t + 3$ = April 2020 (trough)



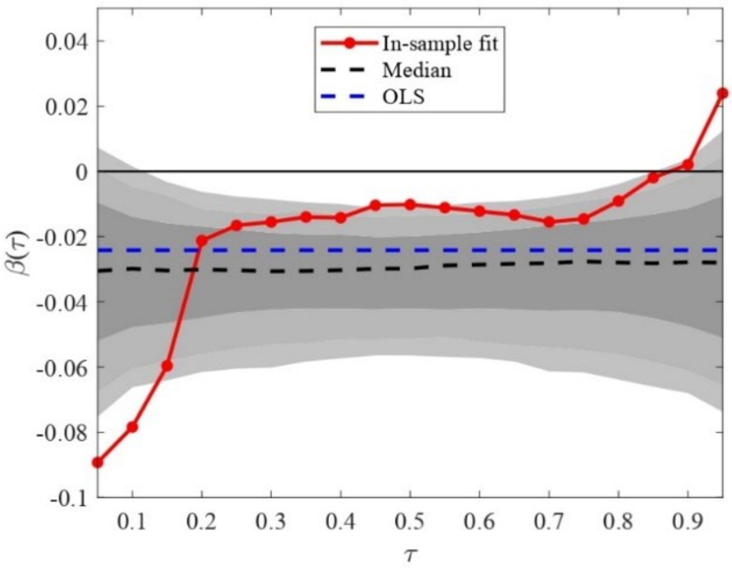
Considering both samples, *Figure 8* shows the estimated coefficients in quantile regressions of one-year-ahead OECD+6NME industrial production growth on WTI. The estimated coefficients at the 5^{th} and 10^{th} quantiles fall outside the 95% confidence bands. These results suggest that WTI is informative for predicting one-year-ahead left-tail outcomes, in both samples considered.

Figure 8. One-year-ahead estimated quantile coefficients: WTI

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



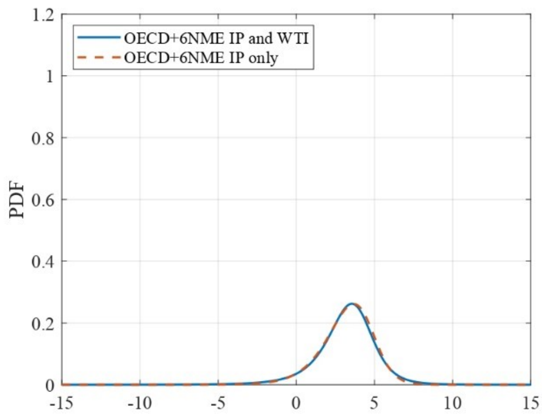
The panels in *Figures 9* and *10* show the estimated PDFs for one-year-ahead OECD+6NME industrial production growth, conditional on current OECD+6NME industrial production growth and WTI, in the selected dates, for the first and second sample respectively. For comparison, we also report the PDFs conditional on current OECD+6NME industrial production growth only.

Figure 9. One-year-ahead probability densities: WTI - first sample

1982 global recession

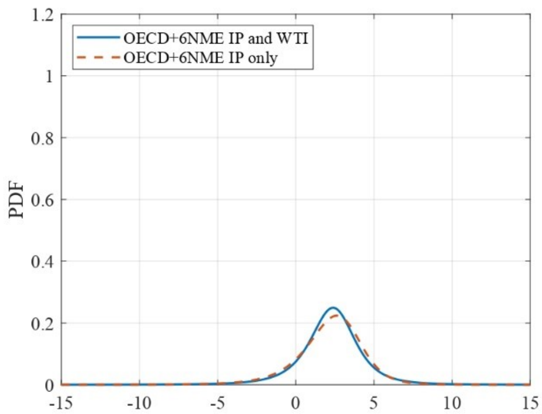
Phase 1

Panel A: $t + 12$ = March 1981 (trough)



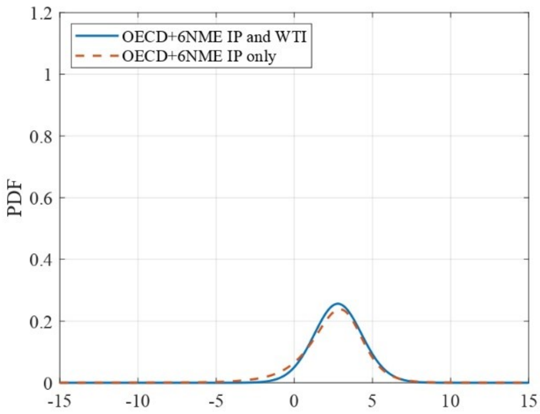
Phase 2

Panel B: $t + 12$ = October 1982 (trough)



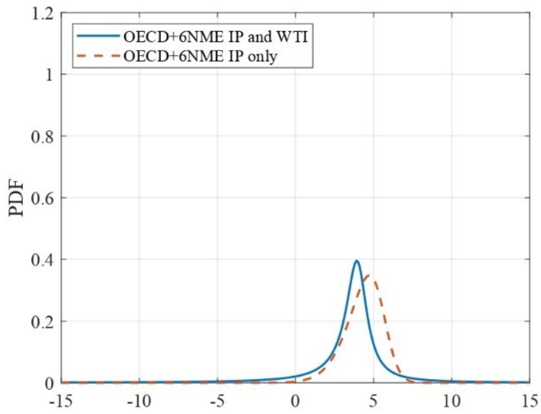
1991 global recession

Panel C: $t + 12$ = March 1991 (trough)



Great Recession

Panel D: $t + 12$ = January 2009 (trough)



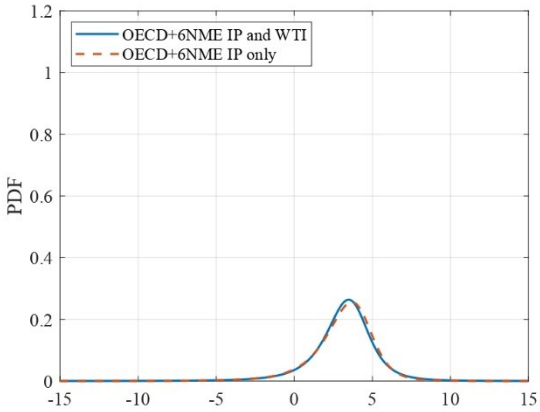
In *Figure 9*, **Panels A**, **B**, and **C** the two conditional distributions display substantially the same behaviour. These results are quite strange, in particular for what concerns the 1982 global recession, which was mainly due to the disruption of the global oil supply. On the other hand, in **Panel D**, the distribution conditional on both OECD+6NME industrial production growth and WTI shows lower mean and variance with respect to the distribution conditional on OECD+6NME industrial production growth only, implying that in the downturn date considered for the Great Recession (i.e., $t + 12$ = January 2009), higher oil prices at time t lower the mean and variance of the OECD+6NME industrial production growth distribution. This mean effect is consistent with the 2007-2008 oil spike suggested by Hamilton (2009) to be an important factor contributing to the early stages of the Great Recession.

Figure 10. One-year-ahead probability densities: WTI - second sample

1982 global recession

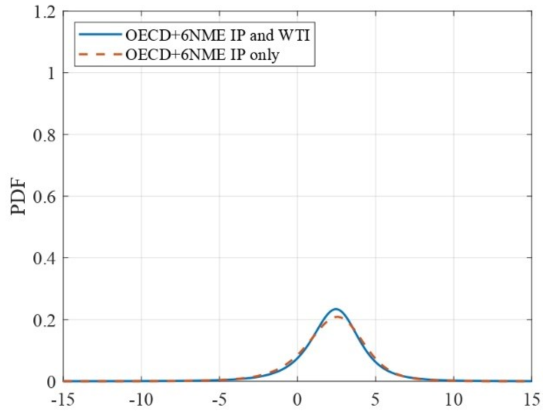
Phase 1

Panel A: $t + 12$ = March 1981 (trough)



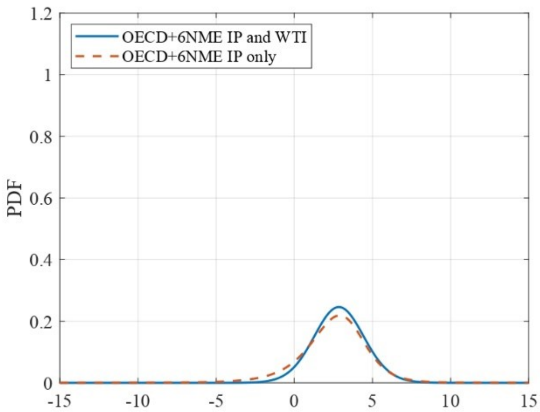
Phase 2

Panel B: $t + 12$ = October 1982 (trough)



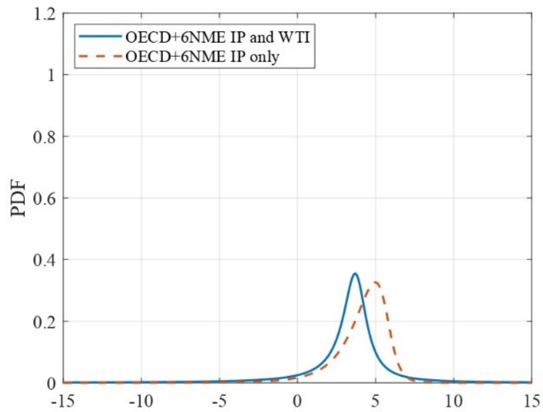
1991 global recession

Panel C: $t + 12$ = March 1991 (trough)



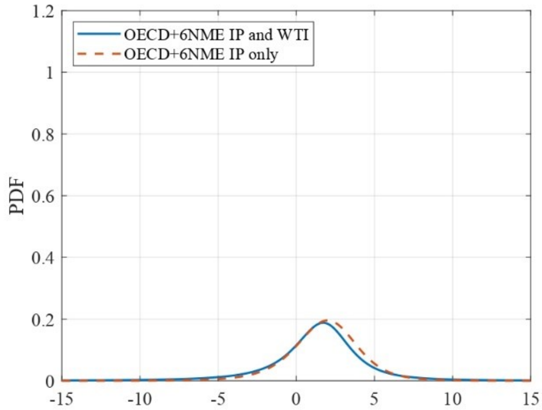
Great Recession

Panel D: $t + 12$ = January 2009 (trough)



Covid-19 global recession

Panel E: $t + 12$ = April 2020 (trough)



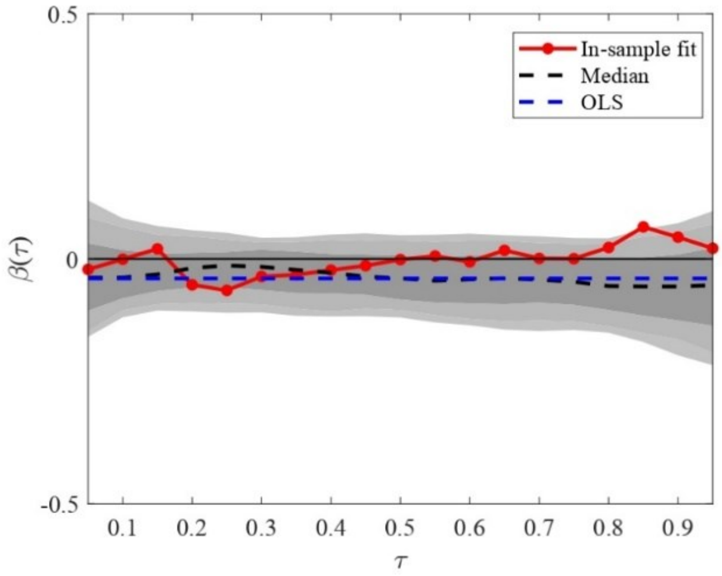
Considering the extended sample, the results are consistent with the ones obtained for the first sample. In particular, in *Figure 10*, **Panel D** the double-conditioned distribution displays lower mean and variance than the single-conditioned one.

4.4 Oil Supply Shocks

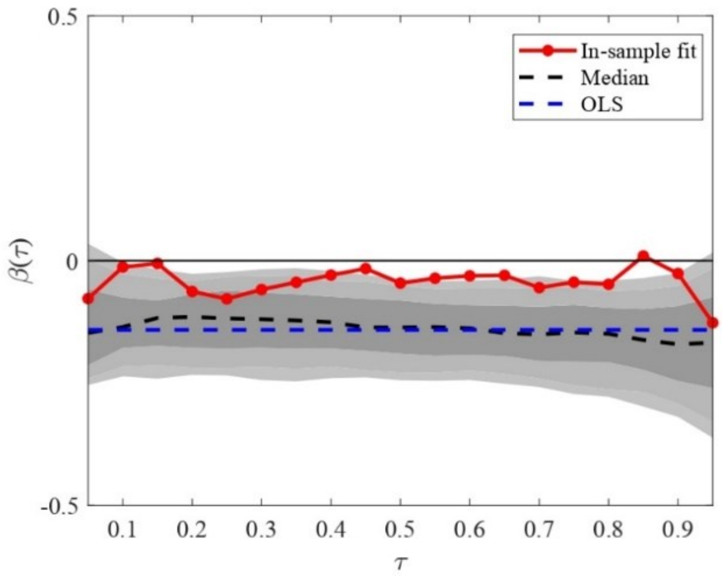
In agreement with the preliminary analysis results, *Figure 11* shows the estimated coefficients in quantile regressions of one-quarter-ahead OECD+6NME industrial production growth on Oil Supply Shocks. Considering the first sample, at lower quantiles, the Oil Supply Shocks coefficients do not result significantly different from the OLS coefficients, suggesting that Oil Supply Shocks are uninformative for predicting left-tail outcomes. This result is strange, especially regarding the 1982 global recession. On the other hand, when considering the extended sample and focusing on the significance at lower quantiles, we observe that the estimated quantile regression coefficient of Oil Supply Shocks at the 15^{th} quantile results slightly significantly different from the OLS coefficients, at the 5% level.

Figure 11. One-quarter-ahead estimated quantile coefficients: OSS

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



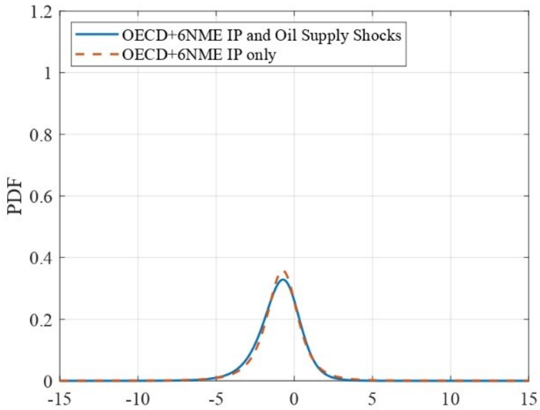
The panels in *Figure 12* show the estimated PDFs for one-quarter-ahead OECD+6NME industrial production growth, with the density estimated conditional on current OECD+6NME industrial production growth and Oil Supply Shocks, in the selected dates, considering the second sample. For comparison, we also report the PDFs conditional on current OECD+6NME industrial production growth only. In all the selected dates, the two conditional distributions display substantially the same behaviour.

Figure 12. One-quarter-ahead probability densities: OSS - second sample

1982 global recession

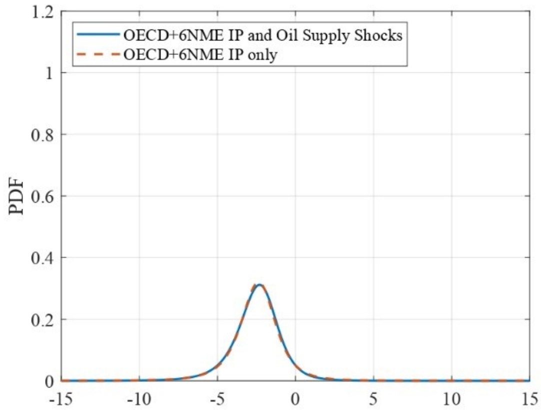
Phase 1

Panel A: $t + 3$ = March 1981 (trough)



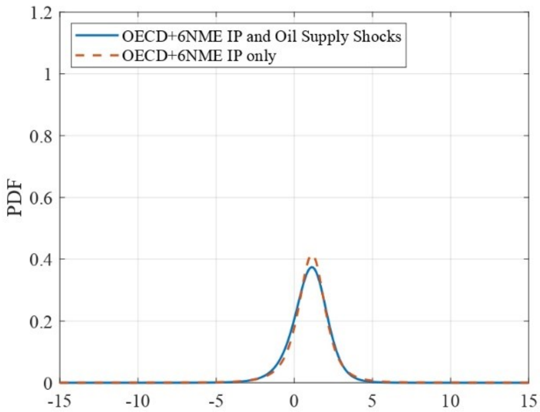
Phase 2

Panel B: $t + 3$ = October 1982 (trough)



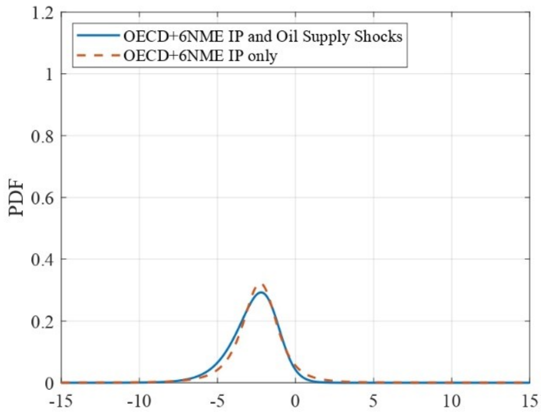
1991 global recession

Panel C: $t + 3$ = March 1991 (trough)



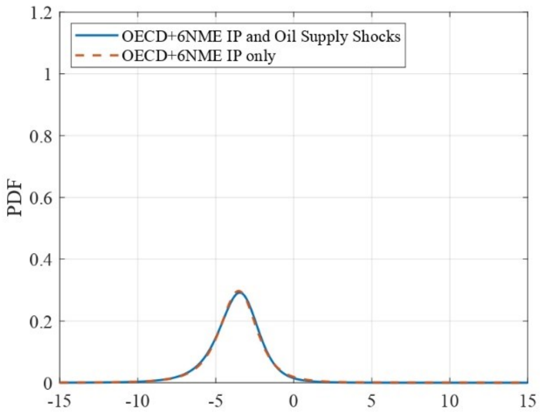
Great Recession

Panel D: $t + 3$ = January 2009 (trough)



Covid-19 global recession

Panel E: $t + 3$ = April 2020 (trough)

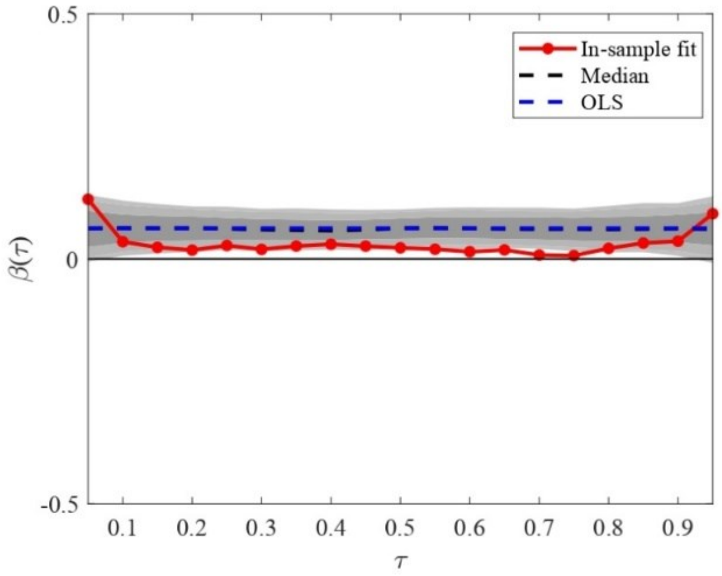


4.5 Oil Consumption Demand Shocks

In the preliminary analysis run considering the sample that ranges from June 1976 to December 2022, the measure of Oil Consumption Demand Shocks results significant at the one-quarter-ahead horizon. Accordingly, *Figure 13* shows the estimated coefficients in quantile regressions of one-quarter-ahead OECD+6NME industrial production growth on Oil Consumption Demand Shocks. The estimated quantile coefficients, in the lower tail, are inside or at the margin of the confidence band for the null hypothesis of a linear relationship and show substantially the same behaviour of the linear ones, suggesting that the quantile regression analysis actually does not add information which a linear model does not provide.

Figure 13. One-quarter-ahead estimated quantile coefficients: OCDS

Second sample: June 1976 – December 2022

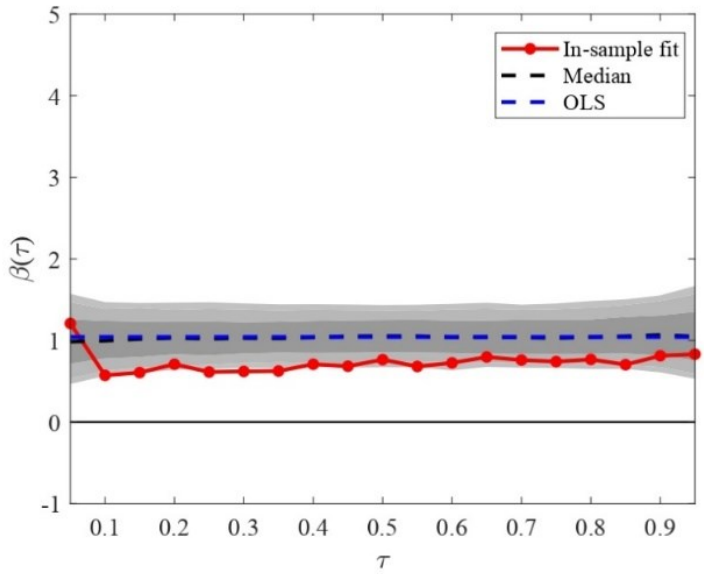


4.6 Real Commodity Price Factor

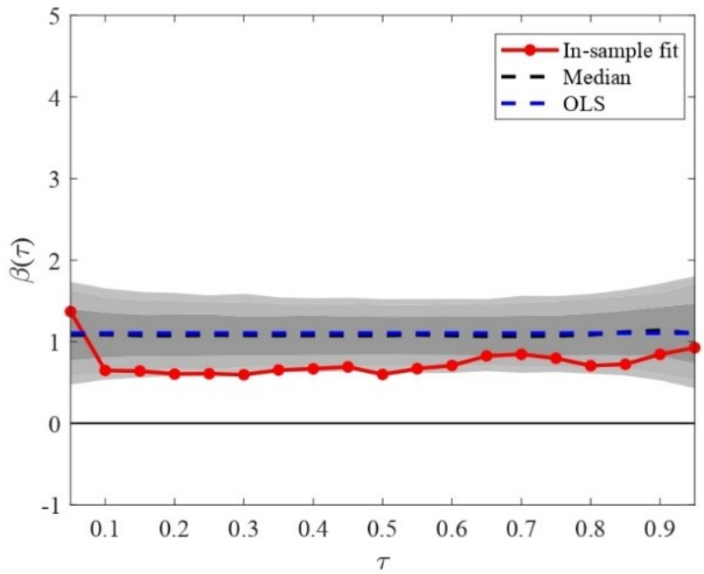
In the preliminary analysis the RCPF coefficients result significant both at the one-quarter- and one-year- ahead horizons. *Figure 14* shows the estimated coefficients in quantile regressions of one-quarter-ahead OECD+6NME industrial production growth on the RCPF. For both samples, at lower quantiles, the estimated quantile coefficients are at the margin of the 95% confidence band for the null hypothesis of a linear relationship. Extending the significance level at the 10%, the estimated coefficients at lower quantiles result slightly significant.

Figure 14. One-quarter-ahead estimated quantile coefficients: RCPF

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



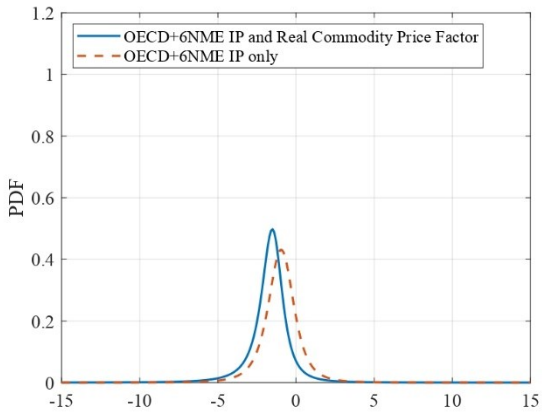
The panels in *Figures 15* and *16* show the estimated PDFs for one-quarter-ahead OECD+6NME industrial production growth, with the density estimated conditional on current OECD+6NME industrial production growth and RCPF in the selected dates, for the first and second sample, respectively. We also plot the PDFs conditional on current OECD+6NME industrial production growth only.

Figure 15. One-quarter-ahead probability densities: RCPF - first sample

1982 global recession

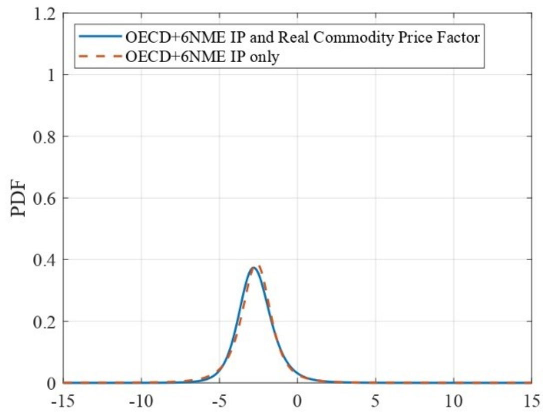
Phase 1

Panel A: $t+3$ = March 1981 (trough)



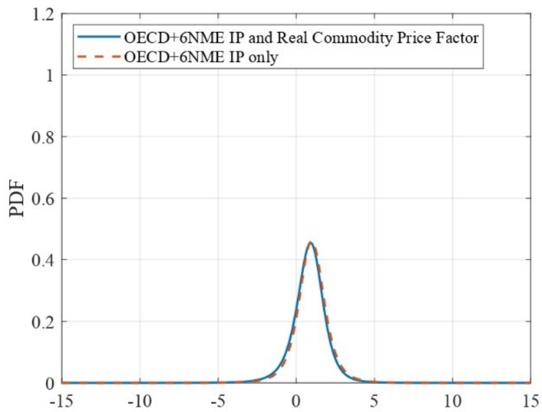
Phase 2

Panel B: $t+3$ = October 1982 (trough)



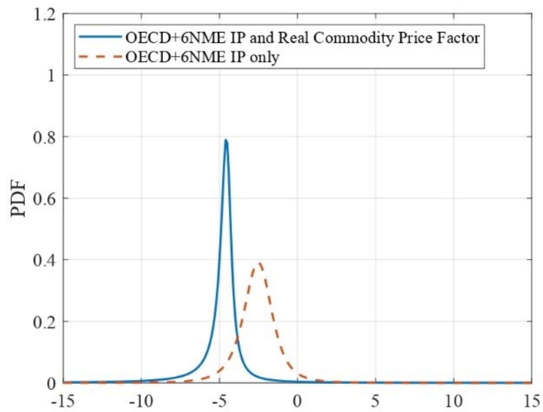
1991 global recession

Panel C: $t+3$ = March 1991 (trough)



Great Recession

Panel D: $t+3$ = January 2009 (trough)



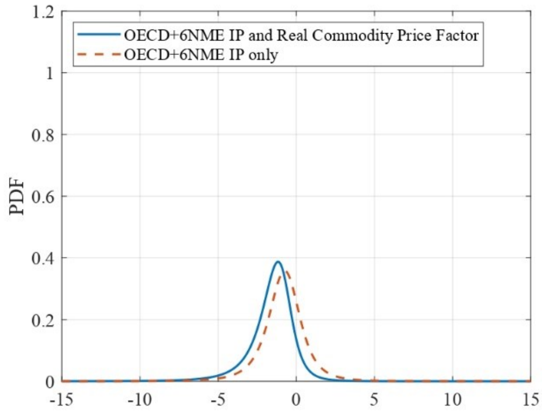
Comparing the conditional densities across the "trough" dates in *Figure 15*, we see that in the second phase of the 1982 global recession (**Panel B**) and in the 1991 global recession (**Panel C**) the two conditional distributions basically display the same behaviour, while in the first phase of the 1982 global recession (**Panel A**) and the Great Recession (**Panel D**) the distribution conditional on both OECD+6NME industrial production growth and RCPF shows lower mean and variance with respect to the distribution conditional on OECD+6NME industrial production growth only. This effect results more pronounced for the Great Recession.

Figure 16. One-quarter-ahead probability densities: RCPF - second sample

1982 global recession

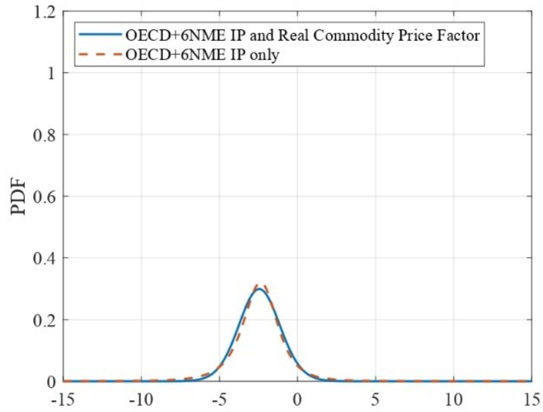
Phase 1

Panel A: $t+3$ = March 1981 (trough)



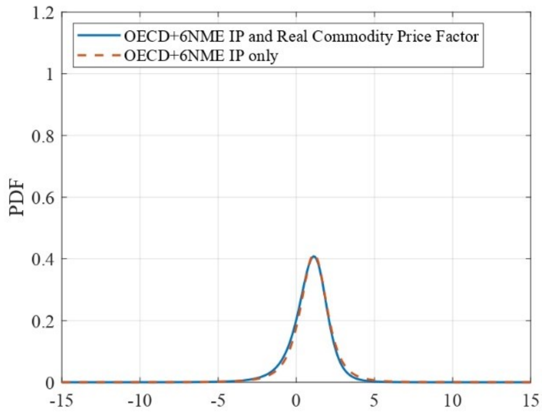
Phase 2

Panel B: $t+3$ = October 1982 (trough)



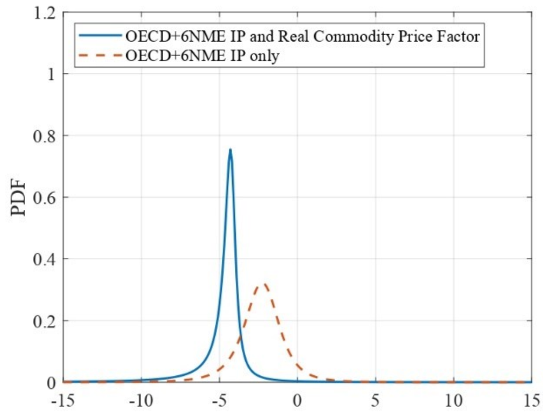
1991 global recession

Panel C: $t+3$ = March 1991 (trough)



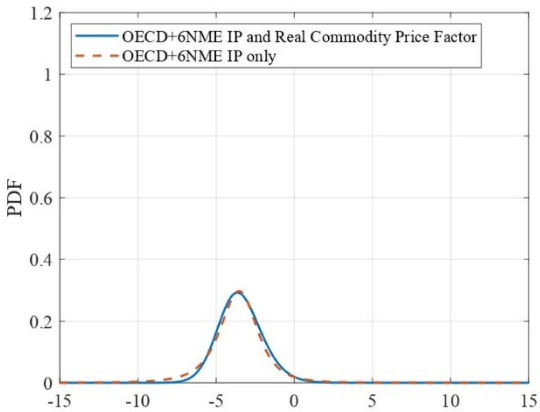
Great Recession

Panel D: $t+3$ = January 2009 (trough)



Covid-19 global recession

Panel E: $t + 3$ = April 2020 (trough)

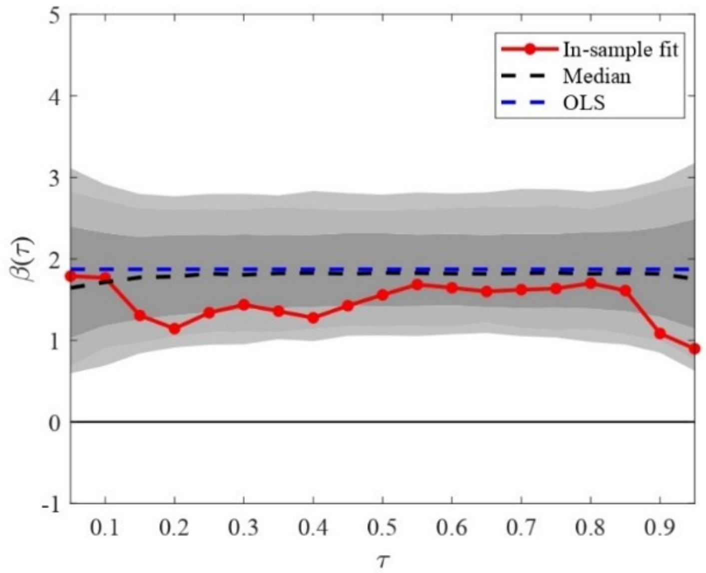


The results showed in *Figure 16* for the second sample are consistent with the ones obtained previously. For what concerns the Covid-19 global recession (**Panel E**) the RCPF does not display any predictive power for OECD+6NME industrial production growth in the "trough" date considered.

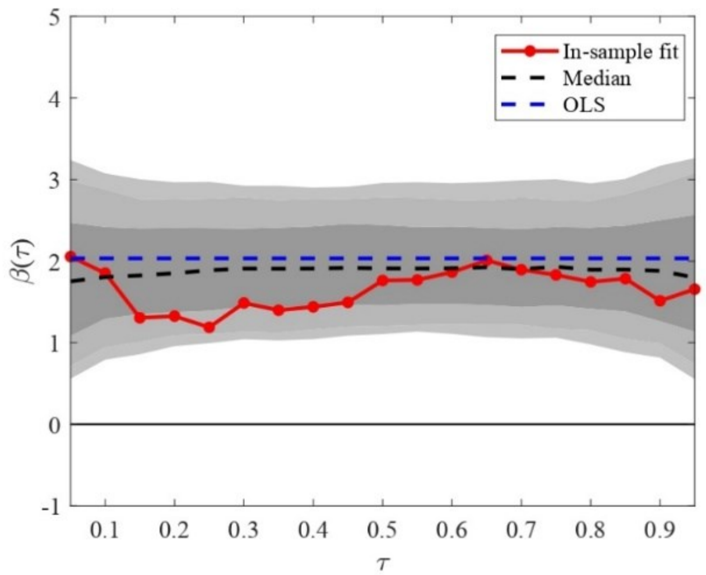
Figure 17 displays the estimated coefficients in quantile regressions of one-year-ahead OECD+6NME industrial production growth on the RCPF. They suggest that the non-linear relationship between future OECD+6NME industrial production growth and the RCPF is muted.

Figure 17. One-year-ahead estimated quantile coefficients: RCPF

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

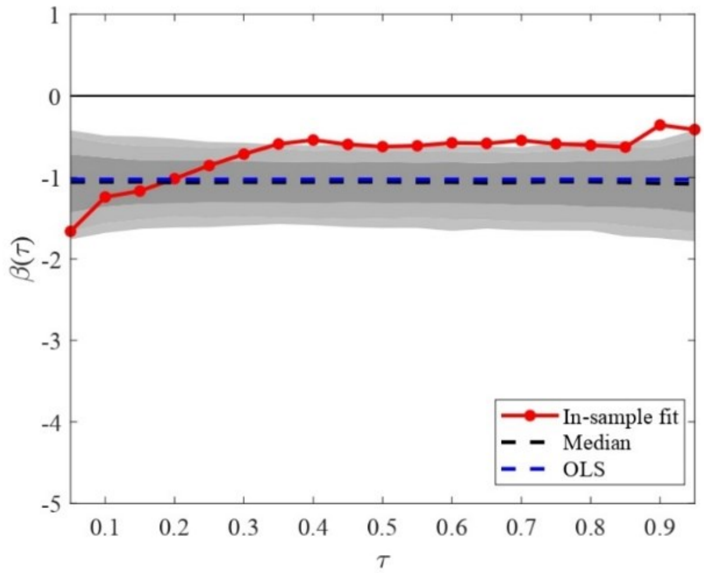


4.7 Excess Bond Premium

In the preliminary analysis the EBP coefficients result significant both at the one-quarter- and one-year- ahead horizons. *Figure 18* shows the estimated coefficients in quantile regressions of one-quarter-ahead OECD+6NME industrial production growth on the EBP. For both samples, at lower quantiles, the estimated quantile coefficients are inside the 95% confidence bands for the null hypothesis of a linear relationship.

Figure 18. One-quarter-ahead estimated quantile coefficients: EBP

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

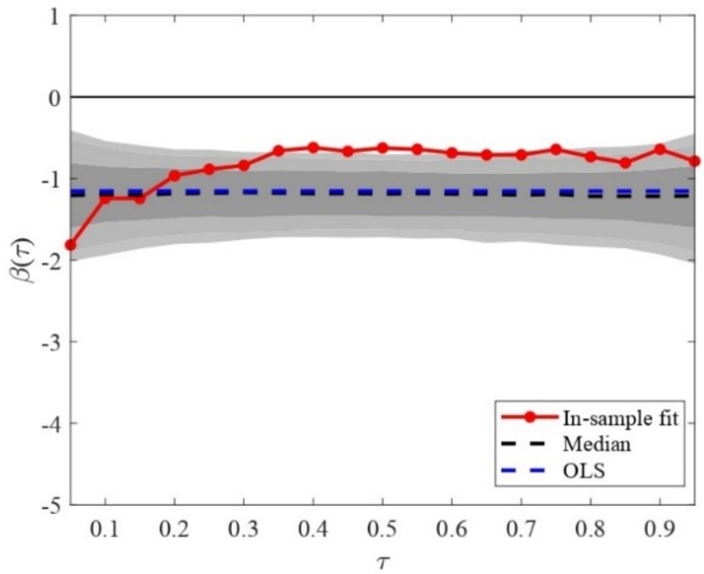
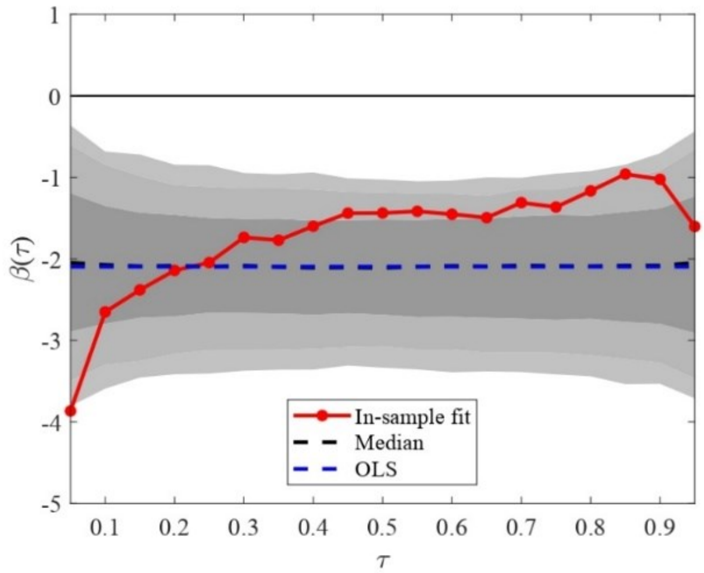


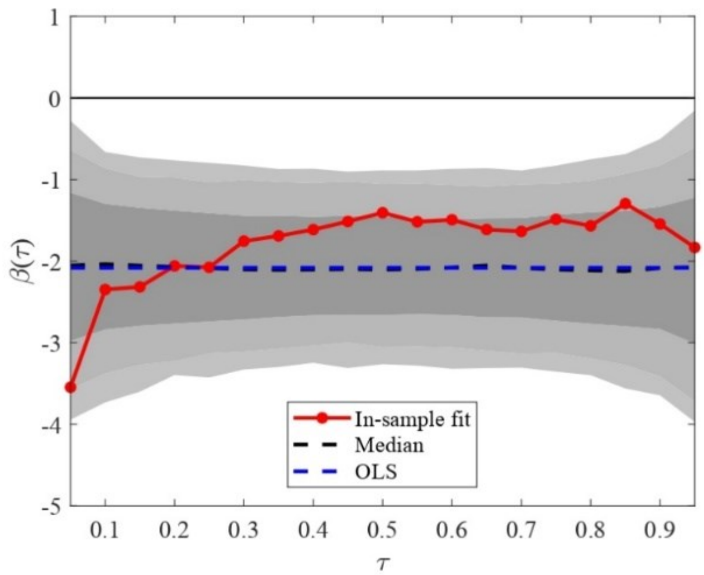
Figure 19 displays the estimated coefficients in quantile regressions of one-year-ahead OECD+6NME industrial production growth on the EBP. For the first sample, the coefficient at the lowest quantile results slightly significantly different, at the 5% level, from the OLS coefficients.

Figure 19. One-year-ahead estimated quantile coefficients: EBP

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



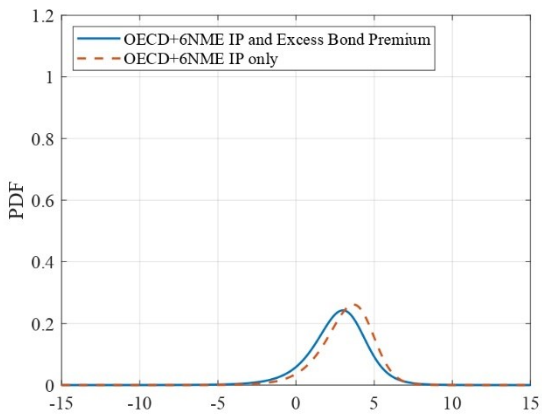
Referring to the first sample, the panels in *Figure 20* show the estimated PDFs for one-year-ahead OECD+6NME industrial production growth, conditional on current OECD+6NME industrial production growth and EBP, in the selected dates. We also report the PDFs conditional on current OECD+6NME industrial production growth only. Comparing the conditional densities across the "trough" dates in *Figure 20*, we see that in all panels the distribution conditional on both OECD+6NME industrial production growth and EBP shows lower mean and higher variance with respect to the one conditional only on OECD+6NME industrial production growth. Moreover, in **Panel D** the double-conditioned distribution is also negatively skewed. These results suggest that frictions in the credit markets are not only first moment but also second moment shocks. Furthermore, for what concerns the Great Recession, they also seem to have a third moment effect. This result is probably related to the financial origin of the Great Recession.

Figure 20. One-year-ahead probability densities: EBP - first sample

1982 global recession

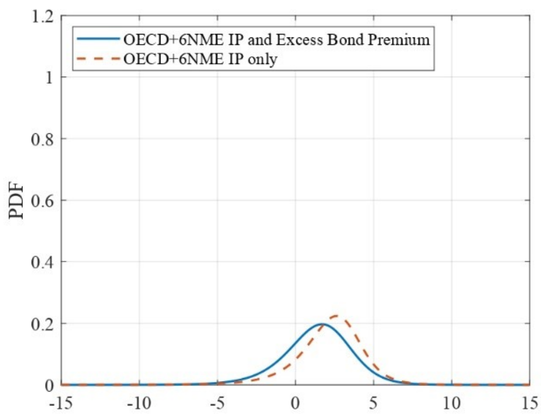
Phase 1

Panel A: $t + 12$ = March 1981 (trough)



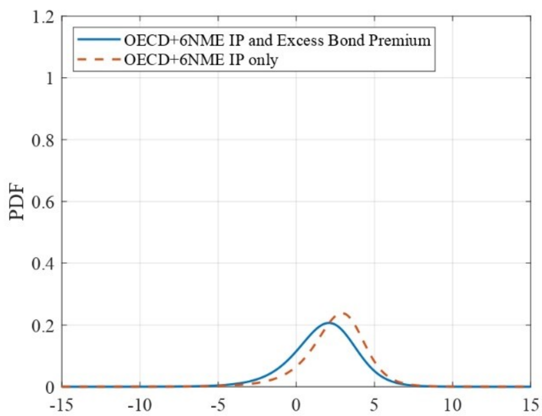
Phase 2

Panel B: $t + 12$ = October 1982 (trough)



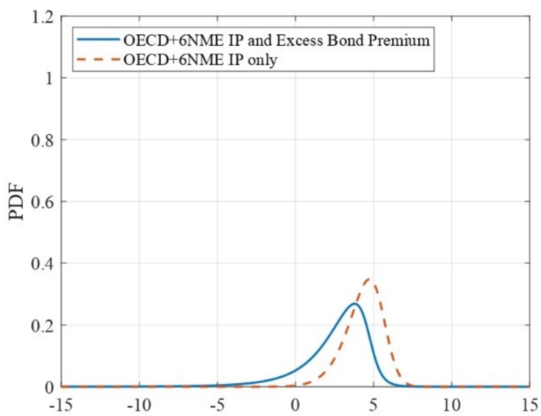
1991 global recession

Panel C: $t + 12$ = March 1991 (trough)



Great Recession

Panel D: $t + 12$ = January 2009 (trough)

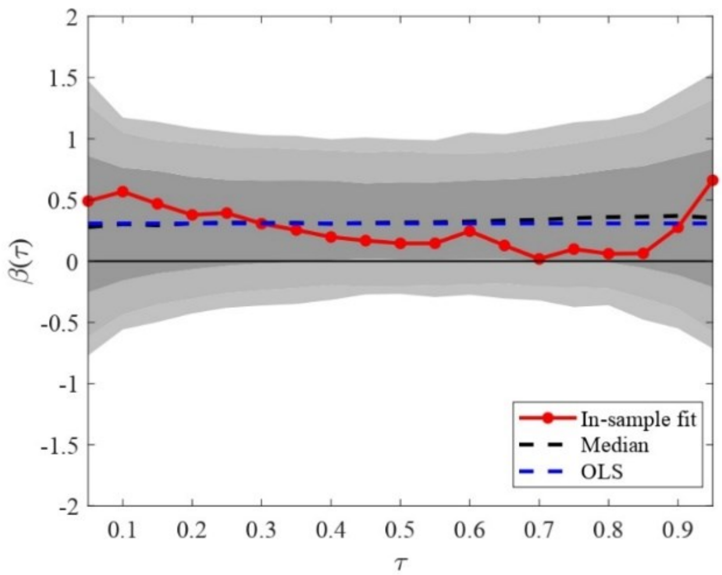


4.8 U.S. Term Spread

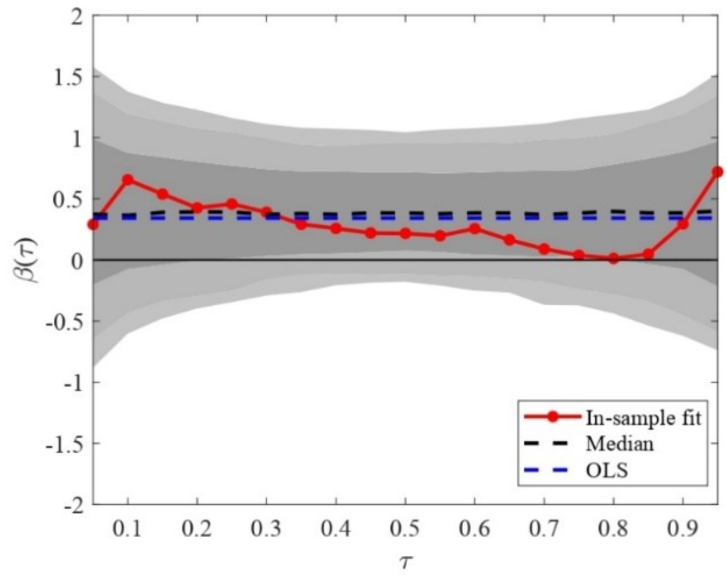
Finally, since the U.S. Term Spread coefficients obtained in the preliminary analysis result significant at the one-year-ahead horizon, *Figure 21* shows the estimated coefficients in quantile regressions of one-year-ahead OECD+6NME industrial production growth on the U.S. Term Spread. The estimated quantile coefficients do not result significantly different form the linear ones, even considering the 68% confidence bands, suggesting that the agents' expectations about the U.S. government solvency are uninformative for predicting tail outcomes.

Figure 21. One-year-ahead estimated quantile coefficients: T10Y2YM

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



5. DOWNSIDE RISK MEASURES

We discuss the behaviour of two downside risk measures: relative downside entropy and 5% expected shortfall. Distinguishing between the two samples, we plot the time series of these two measures for the one-quarter- and one-year- ahead significant predictors which displayed some predictive power in the selected dates. For each recession, we discuss which among these variables predict the largest left-tail movement of the OECD+6NME industrial production growth distribution.

5.1 Downside entropy

According with Adrian, Boyarchenko and Giannone (2019), we quantify the downside risk to the future OECD+6NME industrial production growth as the "extra" probability mass that the conditional density assigns to extreme left-tail outcomes, relative to the probability of these outcomes under the unconditional density. Through the comparison between the probability assigned to extreme outcomes by the conditional density and the probability assigned to the same outcomes by the unconditional density, we evaluate whether the predicted OECD+6NME industrial production growth distribution in a given month implies greater vulnerability in the left tail than the unconditional distribution.

Denoting by $\widehat{g_{y_{t+h}}}$ the unconditional density computed by matching the unconditional empirical distribution of OECD+6NME industrial production growth[20] and by $\widehat{f_{y_{t+h}|x_t}}(y|x_t) = f(y;\ \widehat{\mu_{t+h}}, \widehat{\sigma_{t+h}}, \widehat{\alpha_{t+h}}, \widehat{v_{t+h}})$ the estimated skewed *t*-distribution, the downside entropy, L_t^D, of $\widehat{g_{y_{t+h}}}(y)$ relative to $\widehat{f_{y_{t+h}|x_t}}(y|x_t)$ is given by

$$L_t^D\left(\widehat{f_{y_{t+h}|x_t}};\ \widehat{g_{y_{t+h}}}\right) = -\int_{-\infty}^{\widehat{F^{-1}_{y_{t+h}|x_t}}(0.05|x_t)} \left(\log \widehat{g_{y_{t+h}}}(y) - \log \widehat{f_{y_{t+h}|x_t}}(y|x_t)\right) \widehat{f_{y_{t+h}|x_t}}(y|x_t)\, dy$$

,

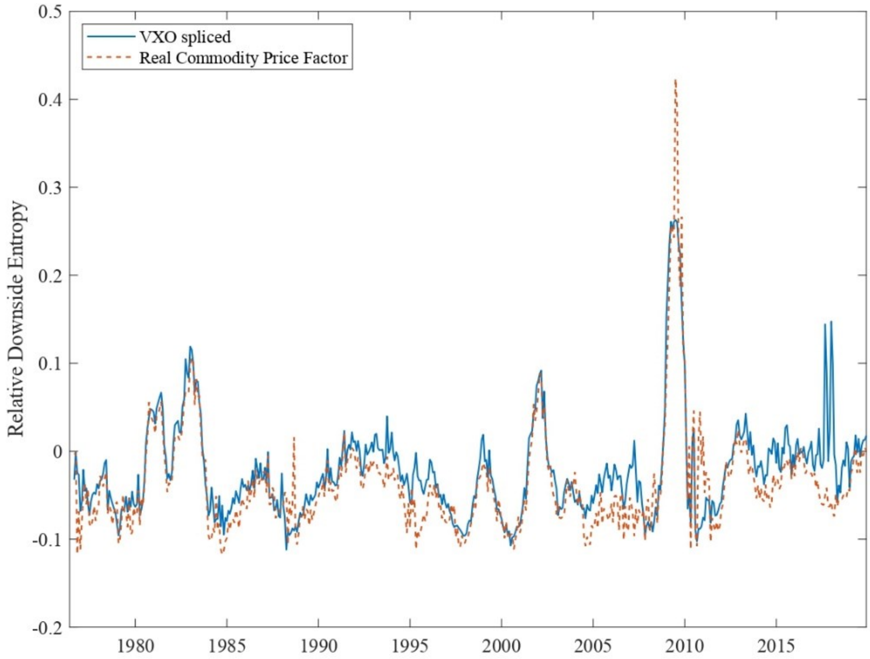
[20] The unconditional density is time invariant and can be computed by performing the two-step procedure where only the constant term is included in the quantile regression of the first step (Adrian, Boyarchenko and Giannone, 2019, p. 1276).

where $\widehat{F_{y_{t+h}|x_t}}(y|x_t)$ is the cumulative distribution associated with $\widehat{f_{y_{t+h}|x_t}}(y|x_t)$ and $\widehat{F^{-1}_{y_{t+h}|x_t}}(0.05|x_t)$ is the conditional 5^{th} quantile. Downside entropy measures the divergence between the unconditional density and the fitted skewed *t*-density that occurs below the 5 percent quantile of the conditional density. When downside entropy is high, the conditional density assigns higher probability to more extreme left-tail growth outcomes than the unconditional density.

Figure 22 shows the downside entropy time series for the one-quarter-ahead significant predictors: VXO spliced and RCPF. In both samples, we see that for the 1982 global recession the downside entropy time series for the two predictors substantially display the same behaviour, with slightly higher peaks of the VXO spliced one. This is true also for the 1991 global downturn. The downside entropy of VXO spliced seems to indicate higher conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, with respect to the RCPF one. Concerning the Great Recession, the RCPF downside entropy shows the highest divergence between the unconditional density and the conditional density below the 5^{th} quantile of the conditional density distribution. In **Panel B**, regarding the Covid-19 global recession, the relative downside entropy of VXO spliced displays a slightly higher peak than the one of the RCPF downside entropy.

Figure 22. Time series evolution of relative downside entropy L_t^D: one quarter ahead

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

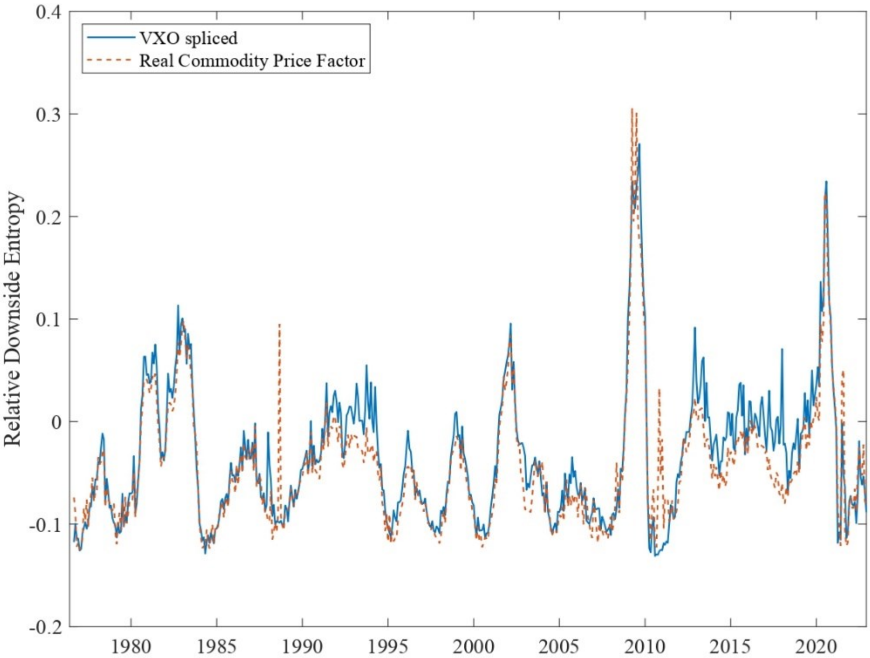
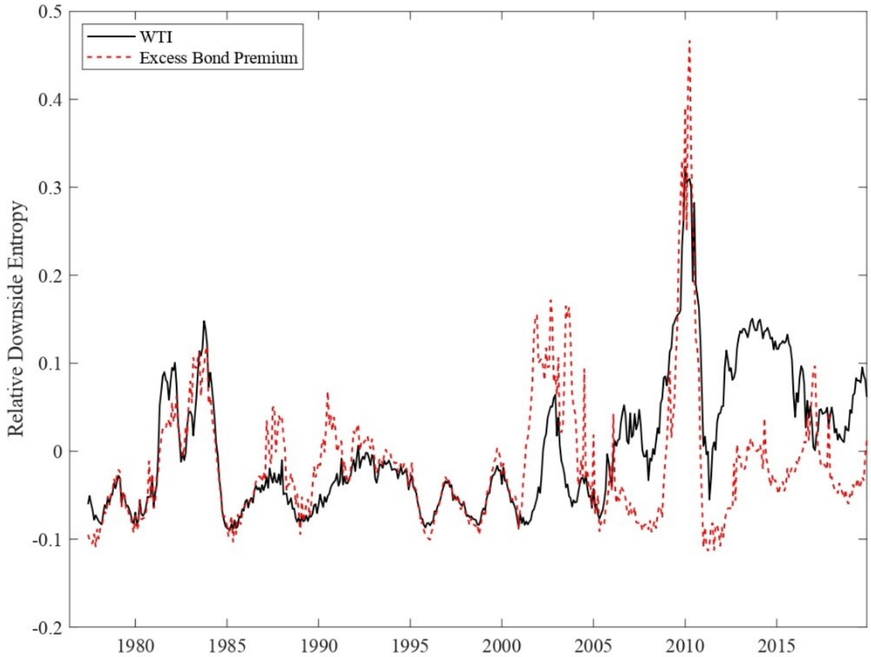


Figure 23. Time series evolution of relative downside entropy L_t^D: one year ahead

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

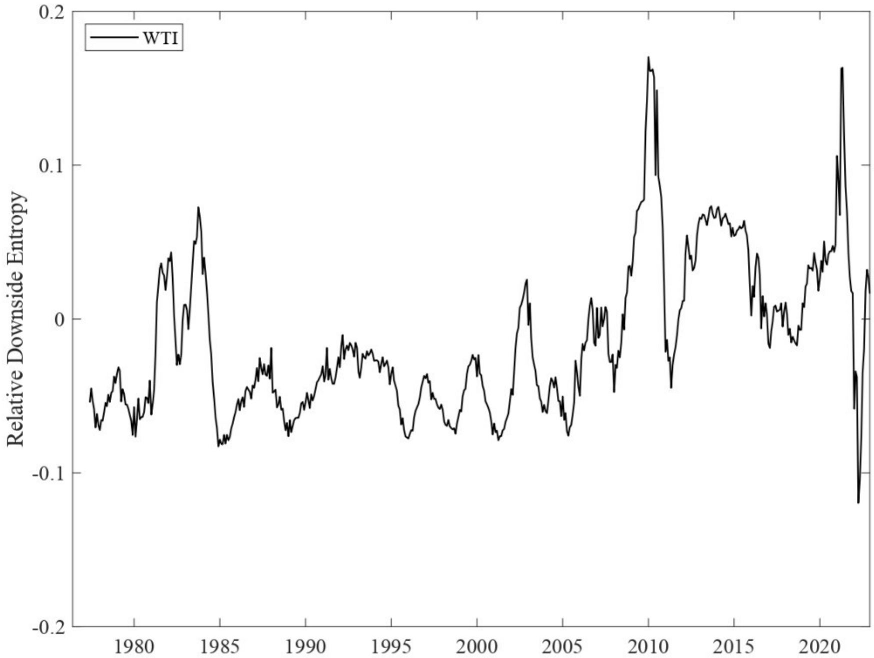


Figure 23 shows the downside entropy time series for the one-year-ahead significant predictors: WTI and EBP. For the second sample, EBP is not considered since it does not result significant at the one-year-ahead horizon. In **Panel A**, we see that for the 1982 global recession the relative downside entropy measure of WTI displays higher peaks, while for the 1991 global downturn and the Great Recession, the EBP downside entropy indicates stronger conditional risks to the downside in excess of the downside risks predicted by the unconditional distribution, with respect to the WTI one. In **Panel B**, in correspondence of the Covid-19 global recession, the downside entropy of WTI displays a peak.

In appendix, *Figures 26A* and *27A* plot the one-quarter- and one-year- ahead downside entropy time series for the significant predictors, with respect to the median of the conditional distribution, according to the definition adopted by Adrian, Boyarchenko and Giannone (2019).

5.2 Expected shortfall

Following Adrian, Boyarchenko and Giannone (2019), we also employ an alternative way of characterizing downside risks to OECD+6NME industrial production growth, in terms of expected shortfall. For a chosen target probability $\pi = 0.05$, the shortfall is defined as

$$SF_{t+h} = \frac{1}{\pi} \int_0^{\pi} \widehat{F_{y_{t+h}|x_t}^{-1}}(\tau|x_t)\, d\tau ,$$

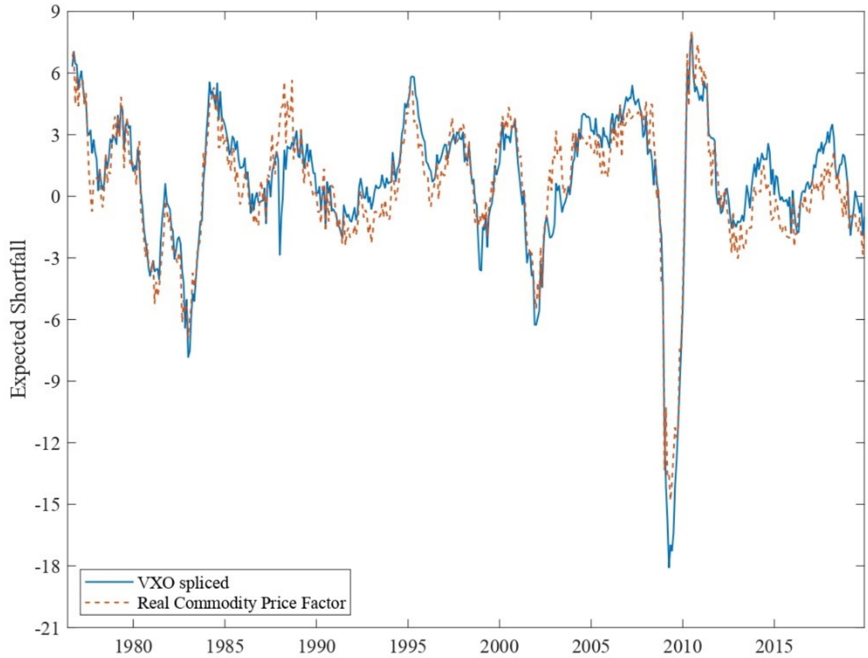
where $\widehat{F_{y_{t+h}|x_t}^{-1}}(\tau|x_t)$ is the fitted inverse cumulative skewed *t*-distribution conditional on x_t. Shortfall summarizes the tail behaviour of the conditional distribution in absolute terms, measuring the total probability mass that the conditional distribution assigns to the left tail of the distribution.

Figure 24 shows the 5% expected shortfall time series for the one-quarter-ahead significant predictors. For what concerns the 1982 global recession, in the first downturn date the RCPF expected shortfall negative spike predicts the highest probability of obtaining extreme negative values of OECD+6NME industrial production growth. While, in the second “trough” date this behaviour is displayed by the VXO spliced expected shortfall. For the 1991 global downturn, the RCPF seems to show the strongest predictive power of negative outcomes in absolute terms, while for the Great Recession and the Covid-19 global recession (**Panel B**), the 5% expected shortfall of VXO spliced displays the lowest values. The result for the Great Recession is consistent with its financial origin.

Figure 25 shows the expected shortfall time series for the one-year-ahead significant predictors. As expected, for the 1982 global recession, WTI displays the strongest predictive power of negative outcomes of OECD+6NME industrial production growth, while for the 1991 global recession the expected shortfalls of the two predictors roughly show the same behaviour, with the EBP one displaying slightly lower peaks. Interestingly, for the Great Recession WTI displays a stronger predictive power of negative outcomes of OECD+6NME industrial production growth with respect to the EBP, in accordance with Hamilton (2009) who suggests that the 2007-2008 oil price increase should be counted as an important factor contributing to the early stages of the Great Recession. In correspondence of the Covid-19 global recession (**Panel B**), the expected shortfall of WTI shows a moderate downward peak.

Figure 24. Time series evolution of the 5% expected shortfall ES_t: one quarter ahead

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

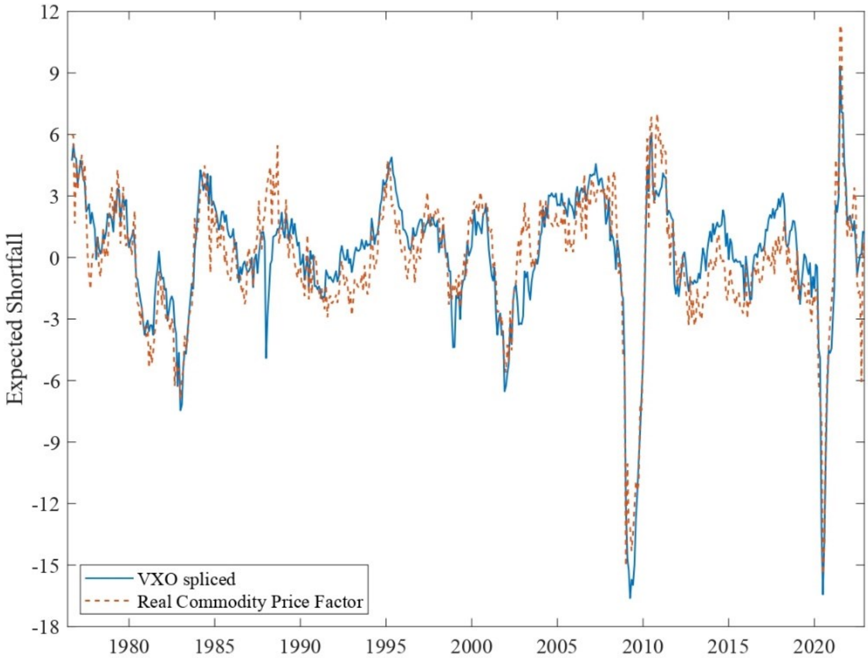
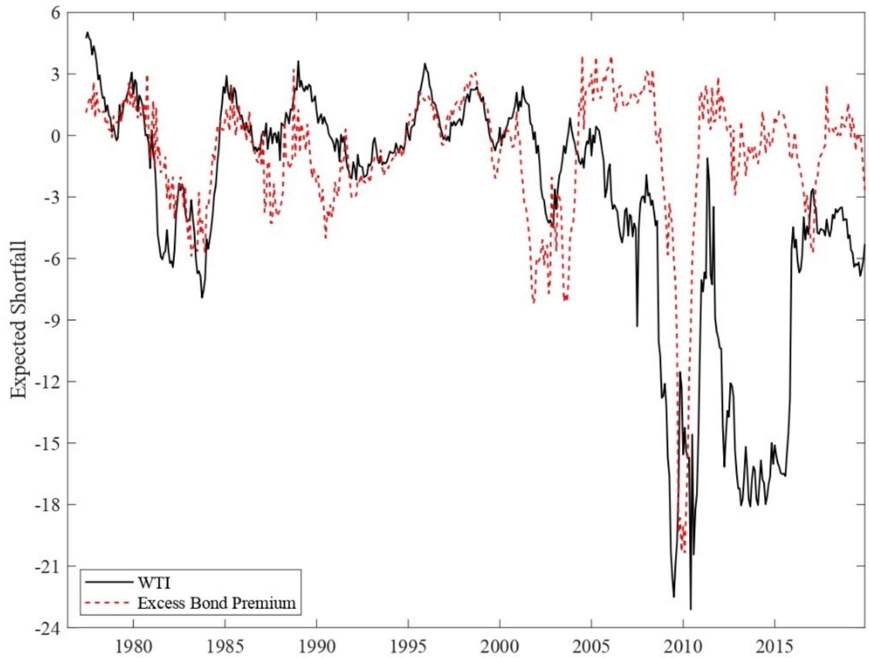
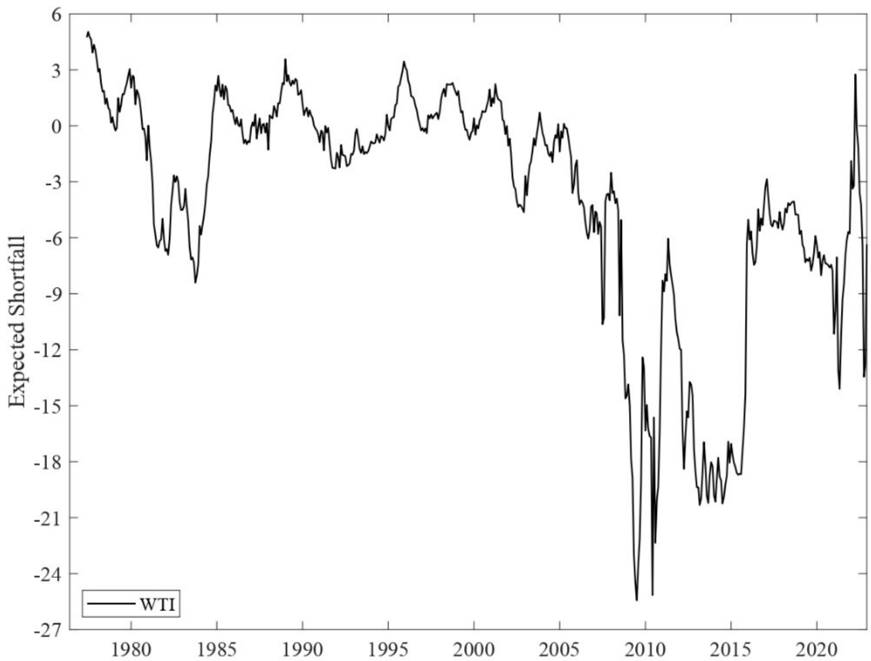


Figure 25. Time series evolution of the 5% expected shortfall ES_t: one year ahead

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



6. CONCLUSION

In this thesis we employed a quantile regression approach to examine the determinants of the last four global recessions, that occurred in 1982, 1991, 2009 and 2020. We considered potential predictive variables of the left tail of the future OECD+6NME industrial production growth conditional distribution, suggested by the financial literature and economic theory. We run the analysis on two samples of monthly data, one excluding the Covid-19 global recession (June 1976 – December 2019), and one including it (June 1976 – December 2022), to see how the results change. Following Adrian, Boyarchenko and Giannone (2019), we investigate which among a group of selected predictive variables show a non-linear relationship with one-quarter- and one-year- ahead world industrial production growth. For those variables for which we rejected the null hypothesis of the existence of a linear relationship, at the 95% confidence level, we plotted the estimated PDFs in the dates in which the OECD+6NME industrial production growth hit the lowest values, in correspondence of each global recession considered, to investigate their left-tail behaviour.

The main finding of this thesis regards volatility inside financial markets. Our proxy measure of financial uncertainty (VXO spliced) seems to be informative about the left-tail behaviour of the one-quarter-ahead OECD+6NME industrial production growth distribution, in particular with reference to the Great Recession. Moreover, only considering the sample which excludes the Covid-19 global recession, also the measure of frictions in the credit markets (EBP) results to be informative at long horizons. In particular, concerning the Great Recession, the results seem to be consistent with the negative effect that frictions in the financial markets had in the run-up to the 2009 global recession. These results seems to imply that adverse financial shocks generate an increase in downside tail risk of future OECD+6NME industrial production growth, consistently with those obtained by Adrian, Boyarchenko and Giannone (2019) for the U.S. and Figueres and Jarociński (2020) for the euro area. Our results contrast with the ones obtained by Plagborg-Møller et al. (2020), who conclude that financial variables have very limited predictive power for the GDP growth distribution at short horizons, especially for what concerns the tail risk.
With regard to our U.S. monetary policy indicator and the U.S. Term Spread, the quantile regression approach does not seem to add information with respect to a linear model about the future OECD+6NME industrial production growth.

Concerning oil market dynamics, our proxy variable of oil prices (WTI) does not display substantial predictive power at short horizons while, considering both samples, at the one-year-ahead horizon it shows a first moment effect only with reference to the 2009 global recession. This is consistent with Hamilton (2009) and Kilian and Hicks (2013) who documented an oil price increase in 2007-2008, attributing it to the strong oil demand from the emerging economies confronting the stagnating global production levels. Strangely, WTI does not display any predictive power for what concerns the 1982 global recession, which is well known for being an oil-price-driven recession. Even the oil shock measures do not seem to be informative to predict extreme negative outcomes of OECD+6NME industrial production growth. For what concerns other commodities, at the one-quarter-ahead horizon, the RCPF seems to display a mean effect regarding the first 1982 global downturn and the 2009 global recession, which is particularly accentuated for the Great Recession.

For the predictive variables considered, the estimated PDFs plotted in the "trough" date of the Covid-19 global recession do not seem to indicate a substantial informative power on future OECD+6NME industrial production growth.

By looking at downside risk measures, it seems that at the one-quarter-ahead horizon the variables that predict the highest probability of observing negative values of OECD+6NME industrial production growth are the Real Commodity Price Factor and VXO spliced for the first and the second downturn of the 1982 global recession, respectively; the Real Commodity Price Factor for the 1991 global recession; VXO spliced for the 2009 and Covid-19 global recessions. At the one-year-ahead horizon, the Excess Bond Premium is the variable that predicts the highest probability of observing extreme left-tail realizations of the world industrial production growth distribution for the 1991 global recession, while for the other global downturns considered, it is WTI.

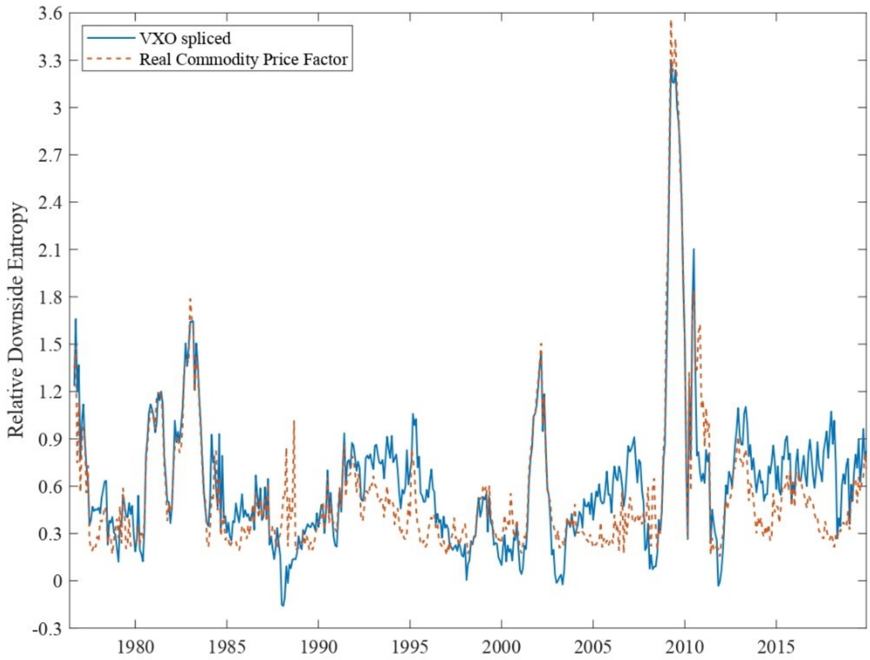
The main finding of this thesis have important policy implications, suggesting that it is necessary for policymakers to monitor global financial market developments and take appropriate regulations to mitigate as much as possible the recessionary effects of uncertainty shocks. Some potential avenues for future research could be pursued employing alternative forecasting approaches and/or expanding the set of predictive variables considered, for example including some measures of global Total Factor Productivity[21] and supply chain[22] shocks (which was not possible to consider in this analysis because of data limitations), to investigate their predictive power, in particular concerning the Covid-19 global recession.

[21] See Huo, Levchenko and Pandalai-Nayar (2018); Cesa-Bianchi, Pesaran and Rebucci (2020).
[22] See Federal Reserve Bank of New York (2023), <https://www.newyorkfed.org/research/policy/gscpi#/overview>.

APPENDIX

Figure 26A. Time series evolution of relative downside entropy L_t^D with respect to the median of the conditional distribution: one quarter ahead

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022

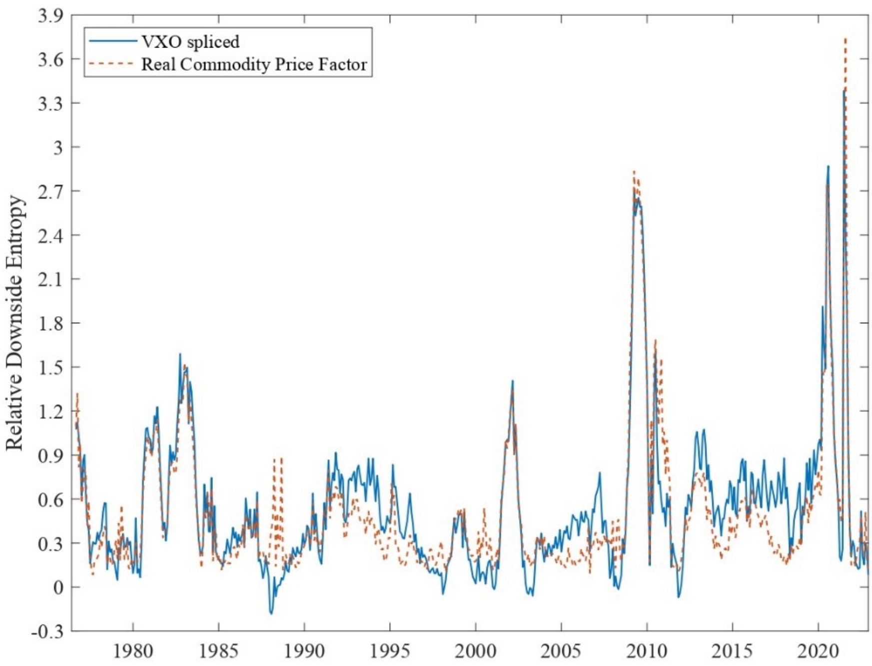
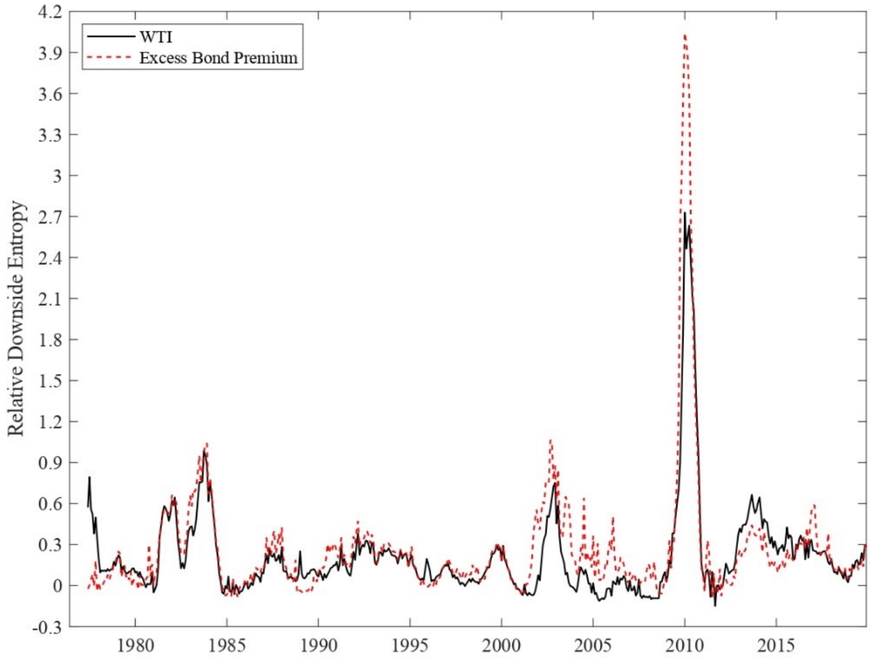
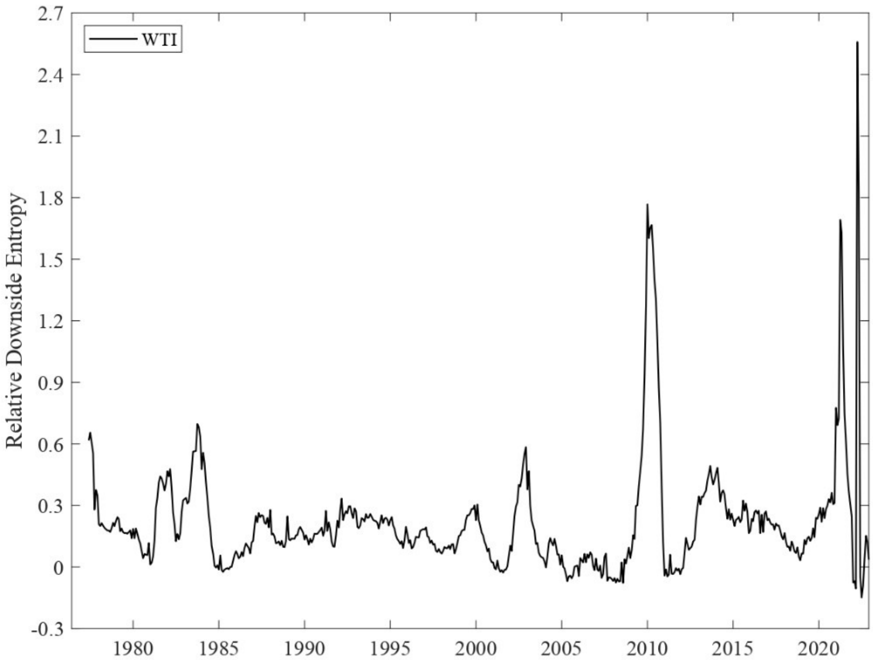


Figure 27A. Time series evolution of relative downside entropy L_t^D with respect to the median of the conditional distribution: one year ahead

Panel A. First sample: June 1976 – December 2019



Panel B. Second sample: June 1976 – December 2022



REFERENCES

ADRIAN, T., BOYARCHENKO, N., GIANNONE, D., 2019. Vulnerable Growth. *American Economic Review*, 109 (4), 1263–1289.

ALESSANDRI, P., MUMTAZ, H., 2019. Financial Regimes and Uncertainty Shocks. *Journal of Monetary Economics*, 101 (C), 31–46.

ALQUIST, R., BHATTARAI, S., COIBION, O., 2020. Commodity-Price Comovement and Global Economic Activity. *Journal of Monetary Economics*, 112 (C), 41–56.

ANDREASEN, M. M., et al., 2023. *Why Does Risk Matter More in Recessions than in Expansions? Implications for Monetary Policy*. Mimeo.

AZZALINI, A., CAPITANIO, A., 2003. Distributions Generated by Perturbation of Symmetry with Emphasis on a Multivariate Skew t-Distribution. *Journal of the Royal Statistical Society Series B: Statistical Methodology,* 65 (2), 367–389.

BAUMEISTER, C., KOROBILIS, D., LEE, T. K., 2022. Energy Markets and Global Economic Conditions. *Review of Economics and Statistics*, 104 (4), 828–844.

BAUMEISTER, C., GUÉRIN, P., 2021. A Comparison of Monthly Global Indicators for Forecasting Growth. *International Journal of Forecasting*, 37 (3), 1276–1295.

BAUMEISTER, C., HAMILTON, J. D., 2019. Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. *American Economic Review*, 109 (5), 1873-1910.

BLACK, F., 1995. Interest Rates as Options. *The Journal of Finance*, 50 (5), 1371-1376.

BLOOM, N., 2009. The Impact of Uncertainty Shocks. *Econometrica*, 77 (3), 623–685.

CAGGIANO, G., CASTELNUOVO, E., 2023. Global Financial Uncertainty. *Journal of Applied Econometrics*, 38 (3), 432-449.

CAGGIANO, G., CASTELNUOVO E., GROSHENNY, N., 2014. Uncertainty Shocks and Unemployment Dynamics in U.S. Recessions. *Journal of Monetary Economics*, 67 (C), 78–92.

CALDARA, D., SCOTTI, C., ZHONG, M., 2021. *Macroeconomic and Financial Risks: A Tale of Mean and Volatility*. International Finance Discussion Papers 1326, Board of Governors of the Federal Reserve System.

CESA-BIANCHI, A., PESARAN, M. H., REBUCCI, A., 2020. Uncertainty and Economic Activity: A Multicountry Perspective. *The Review of Financial Studies*, 33 (8), 3393–3445.

DELLE CHIAIE, S., FERRARA, L., GIANNONE, D., 2022. Common Factors of Commodity Prices. *Journal of Applied Econometrics*, 37 (3), 461-476.

ENGEMANN, K. M., KLIESEN, K. L., OWYANG, M. T., 2011. Do Oil Shocks Drive Business Cycles? Some U.S. and International Evidence. *Macroeconomic Dynamics*, 15 (S3), 498–517.

FIGUERES, J. M., JAROCIŃSKI, M., 2020. Vulnerable Growth in the Euro Area: Measuring the Financial Conditions. *Economics Letters*, 191 (C), 109126.

GIGLIO, S., KELLY, B., PRUITT, S., 2016. Systemic Risk and the Macroeconomy: An Empirical Evaluation. *Journal of Financial Economics*, 119 (3), 457–471.

GILCHRIST, S, MOJON, B., 2016. Credit Risk in the Euro Area. *Economic Journal*, 128 (608), 118–158.

GILCHRIST, S., ZAKRAJŠEK, E., 2012. Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, 102 (4), 1692–1720.

GRANZIERA, E., SEKHPOSYAN, T., 2019. Predicting Relative Forecasting Performance: An Empirical Investigation. *International Journal of Forecasting*, 35 (4), 1636–1657.

HAMILTON, J. D., 2013. Oil Prices, Exhaustible Resources, and Economic Growth. *In*: FOUQUET, R. (ed.). *Handbook of Energy and Climate Change*, chapter 1, 29-63.

HAMILTON, J. D., 2009. Causes and Consequences of the Oil Shock of 2007–08. *Brookings Papers on Economic Activity*, 40 (1 (Spring)), 215-283.

HUO, Z., LEVCHENKO, A. A., PANDALAI-NAYAR, N., 2018. Technology and Non-Technology Shocks: Measurement and Implications for International Comovement. Unpublished Manuscript.

INTERNATIONAL MONETARY FUND, 2017. *Global Financial Stability Report: Is Growth at Risk?*

JIMÉNEZ-RODRÍGUEZ, R., SÁNCHEZ, M., 2005. Oil Price Shocks and Real GDP Growth: Empirical Evidence for some OECD Countries. *Applied Economics*, 37 (2), 201-228.

KILIAN, L., MURPHY, D. P., 2014. The Role of Inventories and Speculative Trading in the Global Market for Crude Oil. *Journal of Applied Econometrics*, 29 (3), 454–478.

KILIAN, L., HICKS, B., 2013. Did Unexpectedly Strong Economic Growth Cause the Oil Price Shock of 2003–2008? *Journal of Forecasting*, 32 (5), 385–394.

KOENKER, R., BASSETT, G. JR., 1978. Regression Quantiles. *Econometrica*, 46 (1), 33-50.

KOSE, M. A., SUGAWARA, N., TERRONES, M. E., 2020. *Global Recessions*. World Bank Policy Research Working Paper 9172.

KWARK, N., LEE, C., 2021. Asymmetric Effects of Financial Conditions on GDP Growth in Korea: A Quantile Regression Analysis. *Economic Modelling*, 94 (C), 351–369.

MERTON, R. C., 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance*, 29 (2), 449-470.

MIRANDA-AGRIPPINO, S., REY, H., 2022. The Global Financial Cycle. *In*: GOPINATH, G., HELPMAN, E., ROGOFF, K. (eds.). *Handbook of International Economics*, 6, chapter 1, 1-43.

MIRANDA-AGRIPPINO, S., REY, H., 2020. The Global Financial Cycle after Lehman. *AEA Papers and Proceedings*, 110, 523-528, American Economic Association.

NG, S., WRIGHT, J. H., 2013. Facts and Challenges from the Great Recession for Forecasting and Macroeconomic Modeling. *Journal of Economic Literature*, 51 (4), 1120-1154.

PLAGBORG-MØLLER, M., et al., 2020. When Is Growth at Risk? *Brookings Papers on Economic Activity*, 2020 (Spring), 167-229.

REICHLIN, L., RICCO, G., HASENZAGL, T., 2020. *Financial Variables as Predictors of Real Growth Vulnerability*. CEPR Discussion Paper DP14322.

WANG, B., LI, H., 2021. Downside Risk, Financial Conditions and Systemic Risk in China. *Pacific-Basin Finance Journal*, 68 (C), 101356.

WEST, K. D., WONG, K., 2014. A factor model for co-movements of commodity prices. *Journal of International Money and Finance*, 42 (C), 289–309.

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.

SITOGRAPHY

FEDERAL RESERVE BANK OF NEW YORK, 2023. *Global Supply Chain Pressure Index (GSCPI)*. Available at <https://www.newyorkfed.org/research/policy/gscpi#/overview> [Access date: 05/09/2023].

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT DATA, 2023. *Industrial production*.
Available at <https://data.oecd.org/industry/industrial-production.htm>
[Access date: 17/07/2023].

THE CONFERENCE BOARD, 2022. *What Is a Global Recession and What Can Trigger It?*
Available at <https://www.conference-board.org/topics/recession/what-is-a-global-recession-and-what-can-trigger-it>
[Access date: 05/09/2023].

THE WORLD BANK (a). *GDP growth (annual %)*.
Available at <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG>
[Access date: 05/09/2023].

THE WORLD BANK (b). *Unemployment, total (% of total labor force) (modeled ILO estimate)*.
Available at <https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS>
[Access date: 05/09/2023].

DATASETS

BAUMEISTER, C., 2023. *Datasets*.
Available at <https://sites.google.com/site/cjsbaumeister/datasets>
[Access date: 08/05/2023].

BOARD OF GOVERNORS OF THE FEDERAL RESERVE SYSTEM, 2016. *Updating the Recession Risk and the Excess Bond Premium*.
Available at <https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html>
[Access date: 03/07/2023].

FEDERAL RESERVE BANK OF ATLANTA, 2022. *Wu-Xia Shadow Federal Funds Rate*.
Available at <https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate>
[Access date: 08/05/2023].

FEDERAL RESERVE ECONOMIC DATA, 2023a. *CBOE Volatility Index: VIX (VIXCLS)*.
Available at <https://fred.stlouisfed.org/series/VIXCLS>
[Access date: 07/08/2023].

FEDERAL RESERVE ECONOMIC DATA, 2023b. *Federal Funds Effective Rate (FEDFUNDS)*.
Available at <https://fred.stlouisfed.org/series/FEDFUNDS>
[Access date: 03/08/2023].

FEDERAL RESERVE ECONOMIC DATA, 2023c. *Spot Crude Oil Price: West Texas Intermediate (WTI) (WTISPLC)*.
Available at <https://fred.stlouisfed.org/series/WTISPLC>
[Access date: 03/07/2023].

FEDERAL RESERVE ECONOMIC DATA, 2023d. *10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity (T10Y2YM)*.
Available at <https://fred.stlouisfed.org/series/T10Y2YM>
[Access date: 03/07/2023].

FEDERAL RESERVE ECONOMIC DATA, 2021. *CBOE S&P 100 Volatility Index: VXO (DISCONTINUED) (VXOCLS)*.
Available at <https://fred.stlouisfed.org/series/VXOCLS>
[Access date: 07/08/2023].