Essays on Tail Risks in Macroeconomics

PhD Thesis Defense

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1. Chapter 1: Introduction
2. Chapter 2: Vulnerable Funding
3. Chapter 3: Daily growth-at-risk: Financial or real drivers? The answer is not always the same
4. Chapter 4: Daily Unemployment at Risk
5. Chapter 5: Forecasting Inflation Risk Around the Globe
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Why do we care about tail macro risks?

- Central banks and international organizations forecast relevant economic variables to guide their policy decisions.
- In recent years, policy has focused on tail risks related to economic variables, and this has motivated the development of new statistical tools to evaluate the likelihood of distress scenarios.
- How can we accurate measure macroeconomic tail risks?
- This is a rather new topic in macro (Giglio et al., 2016; Adrian et al., 2019).

Tail Risks in macro: Growth-at-risk approach

1. "Vulnerable growth" paper of Adrian, Boyarchenko, and Gianone (2019) led an important research in explaining macro risks.
2. It is a tool that provides a tractable estimation of the severity and the likeliood of distress economic scenarios.
3. Very important for practitioners and policy makers: Globally used by regulators and organizations (Prasad et al., 2019; Sánchez and Röhn, 2016).

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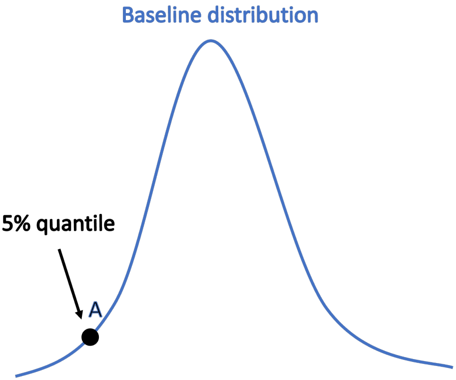
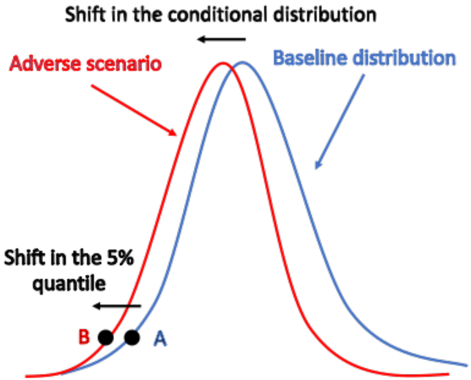
Growth-at-risk: Three important features

1. Inference on quantile coefficients.
2. Point forecasting.
3. Density forecasting.

Growth-at-risk approach (shift in the distribution)





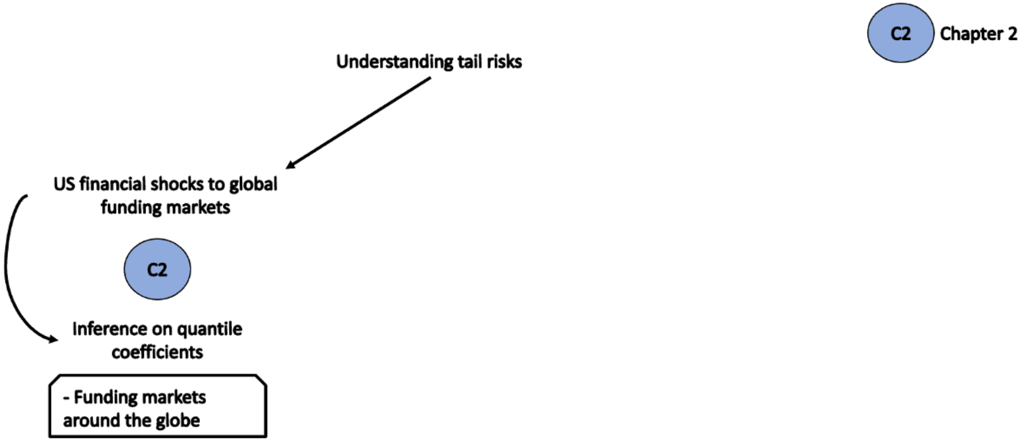
This Thesis

This thesis contributes to our understanding of tail risks in macroeconomics.

General objective

To develop new tools to improve the measurement of tail risks for:
- forecasting purposes,
- and to study the factors that explain tail risks across funding markets economic variables,
- for a specific economy or a broader set of countries.

Road map of this Thesis



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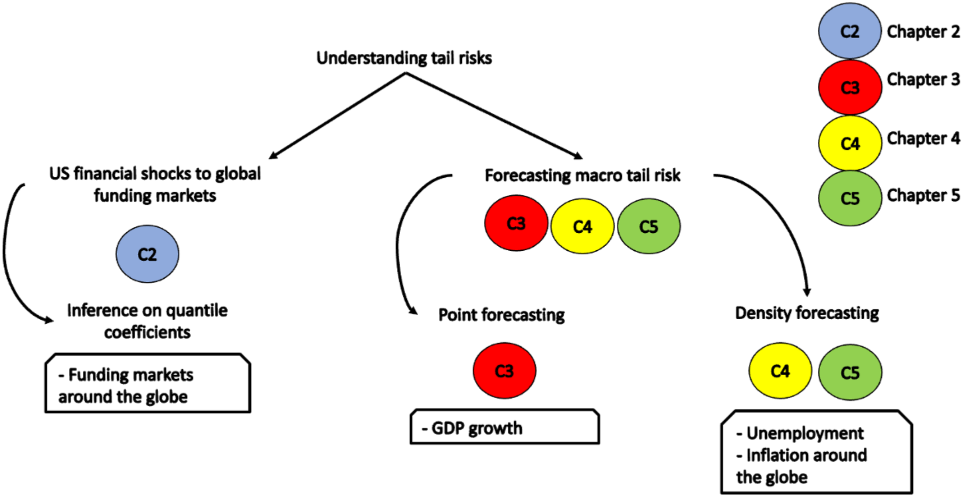

Chapters of this thesis

- **Chapter 2:** Vulnerable Funding in the Global Economy (with H. Chuliá and J.M. Uribe). R&R Journal of Banking and Finance.
- **Chapter 3:** Daily growth-at-risk: financial or real drivers? The answer is not always the same (with H. Chuliá and J.M. Uribe). International Journal of Forecasting, June 2023.
- **Chapter 4:** Monitoring Daily Unemployment at Risk (with H. Chuliá and J.M. Uribe).
- **Chapter 5:** Forecasting Inflation Risk Around the Globe.

Chapter 2: Vulnerable Funding in the Global Economy

Motivation and gap in the literature

- Extensive evidence of "Vulnerable growth" around the globe (e.g., Adrian et al., 2019; Brownlees and Souza, 2021; Figueres and Jarociński, 2020).

- Yet, the **intermediate risk channel** has not been fully explored: how US financial shocks propagate to global financial markets.

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Contribution

GaR literature (Adrian et al., 2019; Brownlees and Souza, 2021; Figueres and Jarociński, 2020)

Two indicators of vulnerable funding are proposed: Credit at Risk (CaR) and Equity at Risk (EaR).

Financial shocks coming from the US (Brave et al., 2011; Ludvigson et al., 2021)

The empirical framework uses two different financial shocks indicators to support our claims: NFCI and FUI.

Impact of US financial shocks on global markets (Kalemli-Özcan, 2019; Alfaro et al., 2004; Di Giovanni et al., 2022)

Cross-sectional determinants of vulnerable funding.

Main findings

1. US financial shocks have a larger and more significant impact on the lowest quantiles of credit and stock prices than on the central and upper quantiles.

2. These effects exhibit considerable heterogeneity across different dimensions:

    - Country under examination,

    - Funding market (credit or stock),

    - Type of shock (whether it is related to financial conditions or financial uncertainty).

3. Funding markets (credit and stocks) with lower credit to GDP, and higher U.S. investment relative to country's GDP are more vulnerable to US financial shocks.

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Methodology: Quantile Regressions

- Augmented quantile-regression models (Koenker and Bassett, 1978; Koenker, 2005).
- The base-line specification is given by Equation 1:

$$\underbrace{y_{it+h}}_{\text{Credit or stock}} = \beta_{0i}(\tau) y_{it} + \beta_{1i}(\tau) \underbrace{us.fs_t}_{\text{NFCI or FUI}} + \delta_{1i}(\tau)' \underbrace{X_t}_{\text{Global factors}} + \epsilon_{it}$$

  $i = 1, .., N$ refers to the country, $h = \{0, 1, 4\}$ refers to the forecasting horizon, and $\tau \epsilon (0, 1)$ to the τ-th quantile.
- X_t based on PCA.

Methodology: Cross-sectional determinants

Cross-secional regressions for each τ and h:

$$\underbrace{\color{blue}{\beta_{1i,\tau}}}_{\color{blue}{\text{Vulnerability}}} = \beta_{1,\tau} + \beta_{2,\tau} * \underbrace{\overline{Credit/GDP_i}}_{\color{red}{\text{Financial depth}}} + \beta_{3,\tau} * \underbrace{\overline{US.FDI_i}}_{\color{green}{\text{US FDI on country i}}} + \epsilon_i$$

Data

1. Long quarterly macro and finance database from 1960Q1 to 2019Q4 (Monnet and Puy, 2019).
    - Global financial factor (N=89; T=240) contains real credit growth, stock returns and changes in sovereign bond yields.
    - Global macroeconomic factor (N=174; T=240) also includes real GDP growth, inflation.
    - Real credit growth (N=44) and stock market returns (N=25).
2. National Financial Condition Index (NFCI) from 1971Q1 to 2019Q4[1].
3. Financial uncertainty indicator (Ludvigson et al., 2021) from 1960Q3 to 2019Q4[2].
4. Credit (or market capitalization)-to-GDP(N=44(25),1960-2019) US direct investment abroad/GDP (N=44,1989-2019).

[1] https://www.chicagofed.org/publications/nfci/index
[2] https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes

Results for Credit-at-risk

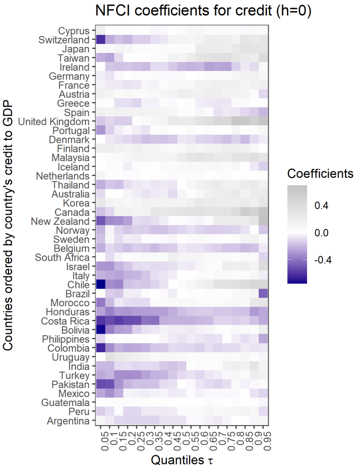
$$\underbrace{y_{it+h}}_{\text{Real credit growth}} = \beta_{0i}(\tau)y_{it} + \beta_{1i}(\tau)\underbrace{us.fs_t}_{\text{NFCI}} + \delta_{1i}(\tau)' \underbrace{X_t}_{\text{Global factors}} + \epsilon_{it}$$

$i = 1, .., 44$ refers to the country, $h = \{0, 1, 4\}$ refers to the forecasting horizon, and $\tau\epsilon(0, 1)$ to the τ-th quantile.

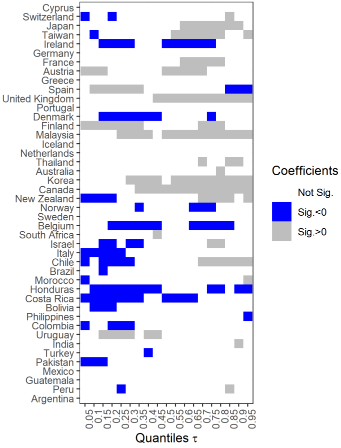
We standardized all the variables to compare the magnitude and sign of the effects across different countries.

Result 1: Coefficients $\beta_{1i}(\tau)$ for $h = 0$

Countries ordered by Credit-to-GDP (descendent)



Note: Model with controls.



Note: Sig. at 90%.

Results for Equity-at-risk

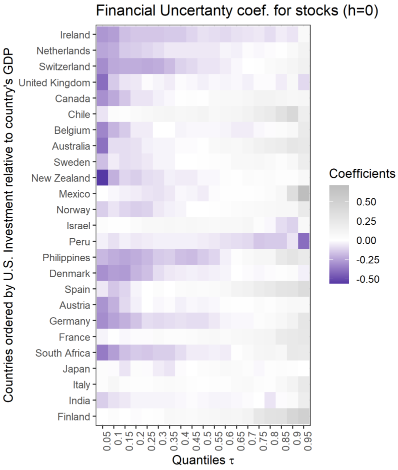
$$\underbrace{y_{it+h}}_{\text{Stocks prices growth}} = \beta_{0i}(\tau)y_{it} + \beta_{1i}(\tau)\underbrace{us.fs_t}_{\text{FUI}} + \delta_{1i}(\tau)' \underbrace{X_t}_{\text{Global factors}} + \epsilon_{it}$$

$i = 1, .., 25$ refers to the country, $h = \{0, 1, 4\}$ refers to the forecasting horizon, and $\tau \epsilon (0, 1)$ to the τ-th quantile.

We standardized all the variables to compare the magnitude and sign of the effects across different countries.

Result 2: Coefficients $\beta_{1i}(\tau)$ for $h = 0$

Countries ordered by U.S. investment relative to country's GDP (descendent)



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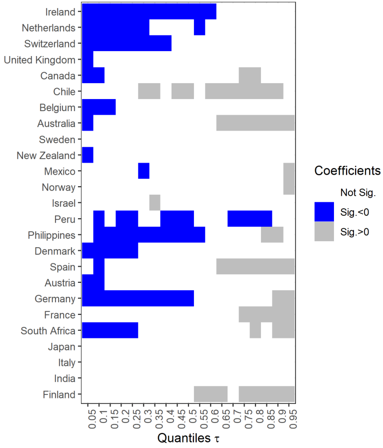

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Chapter 3: Daily growth-at-risk: Financial or real drivers? The answer is not always the same

Motivation and gap in the literature

- Despite the popularity of the framework developed by Adrian et al. (2019), its forecasting performance has not been extensively studied for many settings.
- Lack of consensus in the literature: Financial or real variables? (Plagborg-Møller et al., 2020; Reichlin et al., 2020; Carriero et al., 2022).
- Few evidence on the role of high-frequency indicators in tail risks (Ferrara et al., 2022; De Santis and Van der Veken, 2020).

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Contribution

GaR literature: Financial or Real drivers? (Carriero et al., 2022; Plagborg-Møller et al., 2020; Reichlin et al., 2020)

The informational content of daily financial and real economy indicators differs across time

Forecasting GaR literature (Brownlees and Souza, 2021; Carriero et al., 2022)

High-frequency daily financial and real indicators in pseudo real-time.

Main findings

1. It introduces a daily growth-at-risk (GaR) approach based on high-frequency financial and real indicators for monitoring downside risks in the US economy.
2. It shows that the relative importance of these indicators in terms of their forecasting power is time varying.
3. The LASSO-quantile (LASSO-Q) model outperforms other alternatives proposed in the literature, for example, traditional MIDAS quantile regression,
4. Equity market volatility, credit spreads, and the Aruoba–Diebold–Scotti business conditions index are found to be relevant indicators for nowcasting economic activity, especially during episodes of crisis.

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Data: Real Indicators

Real-time sample spans the period from Jan. 1, 1986 to Dec. 31, 2020.

1. Real Gross Domestic Product (GDP) collected in real-time.
2. ADS index weekly vintages collected in real-time from November 30, 2008.

Data: Financial Indicators

1. Interest rate spread (ISPREAD).
2. Effective Federal Funds Rate (EEFR).
3. Credit spread (CSPREAD).
4. Term spread (TERM).
5. Spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill (TED).
6. Excess return on the market (RET).
7. Returns on the portfolio of small minus big stocks (SMB).
8. Returns on the portfolio of high minus low book-to-market ratio stocks (HML).
9. Returns on a winner minus loser momentum spread portfolio (MOM).
10. CBOE SP 100 Volatility Index (VXO).
11. Composite Indicator of Systemic Stress (CISS).

Methodology: Nowcasting framework

1. Growth at Risk framework (Adrian et al., 2019) extended to account daily flow of information up to T.

$$\underbrace{Q_\tau(y_T)}_{\text{GDP growth}} = \beta_0(\tau) + \underbrace{\beta_1(\tau)y_{T-1}}_{\text{lagged GDP growth}} + \underbrace{X'_{T-h_d}\delta(\tau)}_{\text{Daily indicator}}$$

2. Point forecasts for each X:

$$GaR_T(10\%) = Q_{0.10}(y_T|y_{T-1}, X_{T-h_d})$$

3. Forecast combination is applied (Stock and Watson, 2004; Andreou et al., 2013).
4. Tick loss evaluation (Diebold and Mariano, 1995; Engle and Manganelli, 2004; Kupiec, 1995).

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Models for $Q_{0.10}(.)$

1. Mixed data sampling quantile model (MIDAS-Q).
2. Bayesian MIDAS (BMIDAS-Q), similar to (Ferrara et al., 2022).
3. LASSO quantile (Belloni and Chernozhukov, 2011).
4. Elastic Net quantile (Zou and Hastie, 2005).
5. Two step LASSO quantile (Lima et al., 2020).
6. Two step Elastic Net quantile (Lima et al., 2020).
7. Adaptive sparse group LASSO (ASGL-Q), (Mendez-Civieta et al., 2021).

LASSO selection of X_{t-hd}

Back

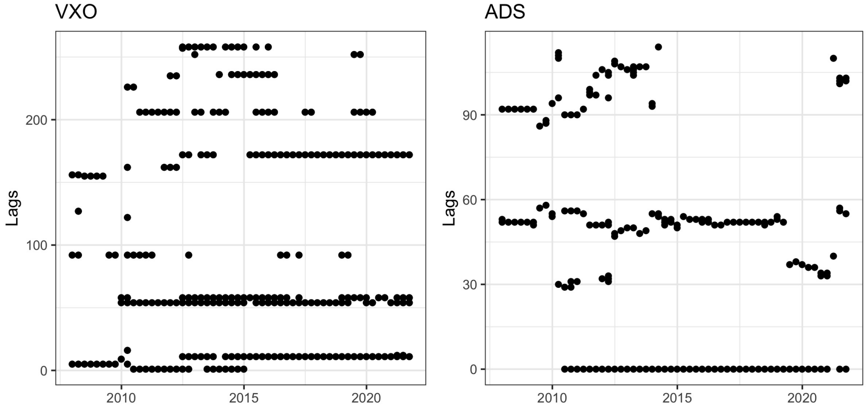
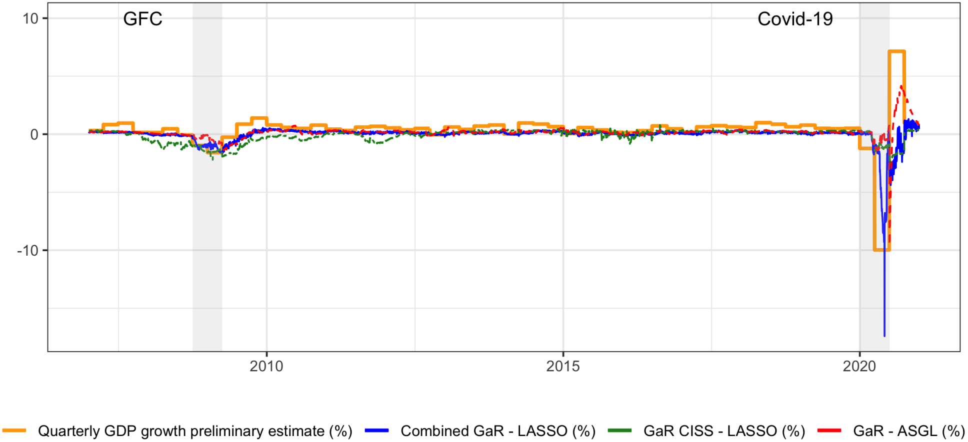


Figure: Lasso selection by the end of quarter

Nowcasting Daily GaR (starting from January 1, 2007)



Daily combination weights for LASSO

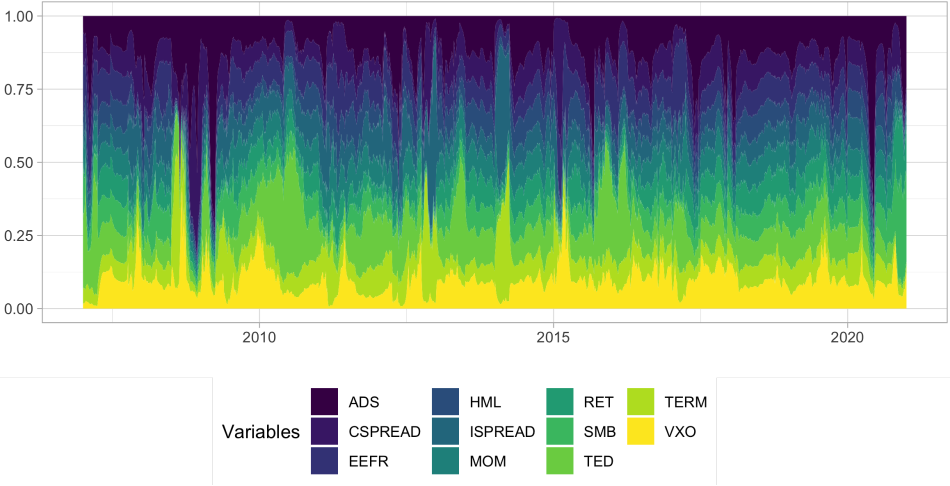


Figure: Daily weights for forecast combination.

Chapter 4: Daily Unemployment at Risk

Motivation and gap in the literature

- Unemployment at risk (Adams et al., 2021; Kiley, 2021).
- Policymakers at The Federal Open Market Committee (FOMC) assess forecasts for unemployment rate.
- Yet, the forecasting errors can be quite sizable during market distress episodes.

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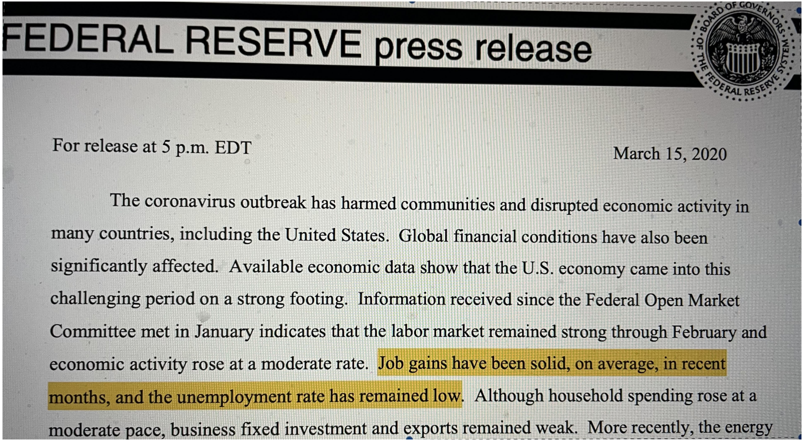
Forecast errors...



FEDERAL RESERVE press release

For release at 5 p.m. EDT

March 15, 2020

The coronavirus outbreak has harmed communities and disrupted economic activity in many countries, including the United States. Global financial conditions have also been significantly affected. Available economic data show that the U.S. economy came into this challenging period on a strong footing. Information received since the Federal Open Market Committee met in January indicates that the labor market remained strong through February and economic activity rose at a moderate rate. Job gains have been solid, on average, in recent months, and the unemployment rate has remained low. Although household spending rose at a moderate pace, business fixed investment and exports remained weak. More recently, the energy

Figure: Extracted from Federal Open Market Committee (2020 March 15)

The next quarter, nonetheless, the average unemployment rate spiked at 13%, the highest increase recorded since 1948!

Figure: Unemployment rate and NBER recession dates

The ESP and the real-time ADS are negatively related.

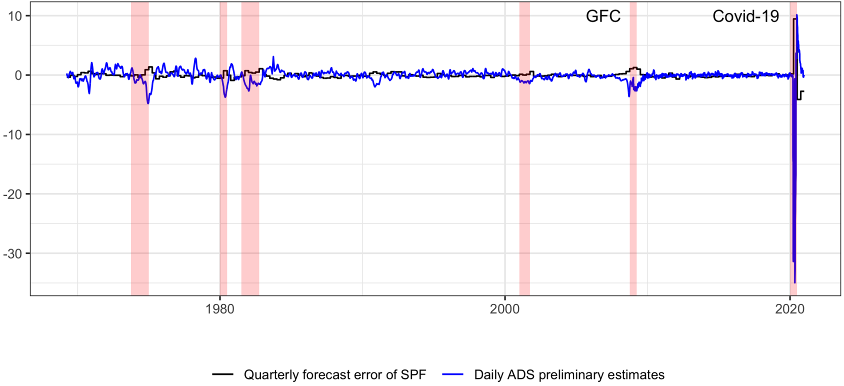


Figure: Evolution of ESP and ADS index (preliminary estimates)

Contribution

Extends Adams et al. (2021) and Kiley (2021) framework.

Forecasting macroeconomic risks (Adams et al., 2021; Kiley, 2021)

Mixed data sampling quantile model in real-time, similar to Ferrara et al. (2022).

Relation between real activity and unemployment (Okun, 1962; Ball et al., 2017)

Aruoba-Diebold-Scotti Index outperforms other financial indicators.

Main findings

1. This chapter constructs daily unemployment at risk around consensus forecasts conditional on the ADS business conditions index, using a Q-MIDAS model.
2. ADS has better nowcasting properties than those provided by daily financial conditioning variables, and
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Adams et al. (2021) extension to Q-MIDAS

- In the first step, we estimate a Q-MIDAS model using quantile regressions (Koenker and Bassett, 1987):

$$\underbrace{e^{SPF}_{t+1|t}}_{\text{forecast error}} = \alpha_0(\tau) + \underbrace{\hat{X}^{D\,\prime}_{t+1-h_d}\theta(\tau)}_{\text{1 year lags of the daily indicator}} + \epsilon_t \tag{1}$$

- $\tau = 0.05, 0.25, 0.75, 0.95.$

- In this formulation the forecast horizon is expressed in high-frequency terms.

Q-MIDAS

- The one-step-ahead forecast of unemployment for a particular τ is:

$$\underbrace{\hat{Q}_\tau(y_{t+1}|\hat{X}^D_{t+1-h_d})}_{\text{Unemployment forecast}} = \underbrace{\hat{Q}_\tau(e^{SPF}_{t+1|t}|\hat{X}^D_{t+1-h_d})}_{\text{conditional quantile of Eq.1}} + \underbrace{y^{SPF}_{t+1|t}}_{\text{SPF forecast}}$$

- Then, a skew-t distribution in the spirit of (Adrian et al., 2019).

Daily nowcasts of ADS index in real time

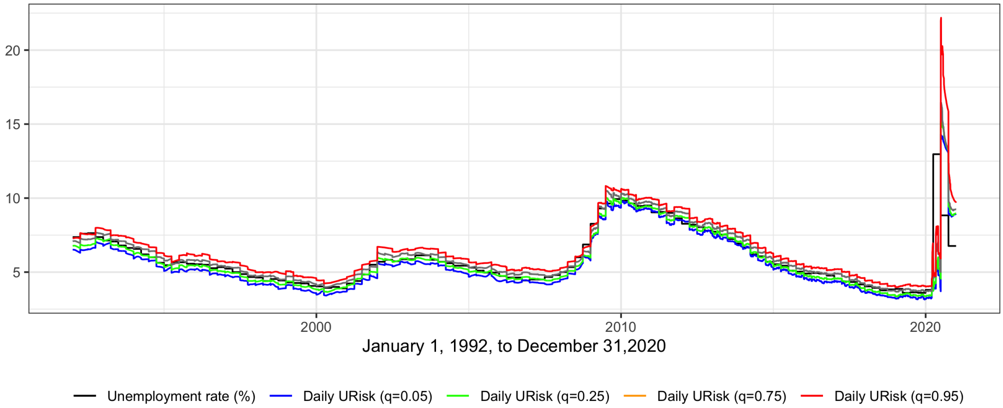

Figure: Historical quantile estimates

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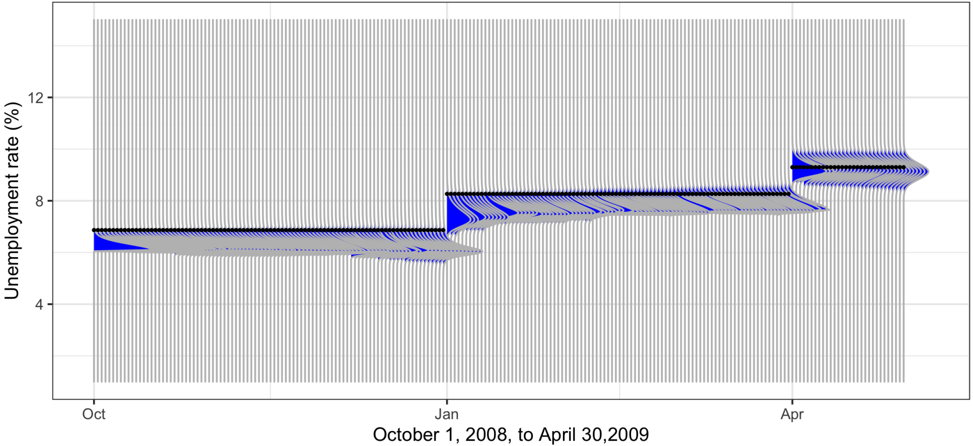

Figure: Global Financial Crisis

Daily nowcasts of ADS index in real time

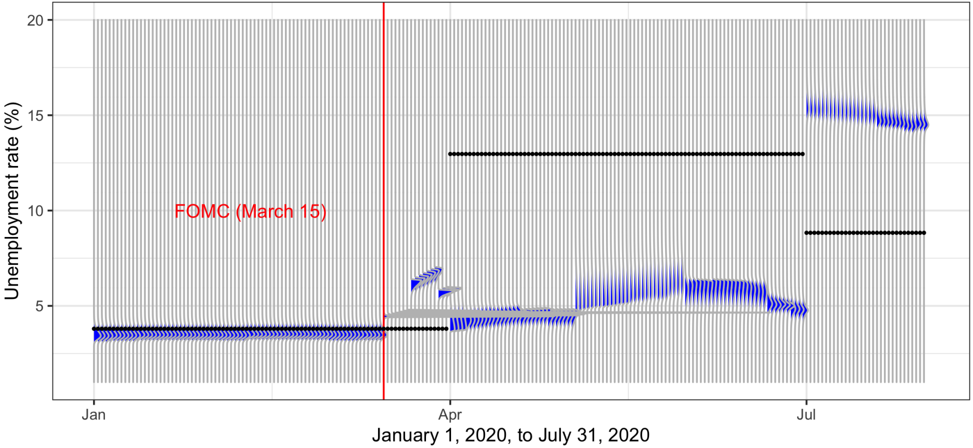

Figure: Covid-19

Chapter 5: Forecasting Inflation Risk Around the Globe

Motivation and gap in the literature

- Inflation at risk is a hot topic (see, e.g., Banerjee et al., 2020; Lopez-Salido and Loria, 2022; Pfarrhofer, 2022; Queyranne et al., 2022).[3]
- Yet, while they offer insights on inflation risk measures, they do not study extensively the **out-of-sample predictive performance** of their measures nor do they **consider specific world regions**.

[3] For instance, Banerjee et al. (2020) estimate inflation-at-risk statistics for 41 advanced and emerging market economies, and Queyranne et al. (2022) for seven Middle East and Central Asian countries.

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- Inflation at risk is a hot topic (see, e.g., Banerjee et al., 2020; Lopez-Salido and Loria, 2022; Pfarrhofer, 2022; Queyranne et al., 2022).[3]
- Yet, while they offer insights on inflation risk measures, they do not study extensively the **out-of-sample predictive performance** of their measures nor do they **consider specific world regions**.

[3] For instance, Banerjee et al. (2020) estimate inflation-at-risk statistics for 41 advanced and emerging market economies, and Queyranne et al. (2022) for seven Middle East and Central Asian countries.

Contribution

Broader set of countries and regions using global factors (e.g. Ciccarelli and Mojon, 2010; Kamber and Wong, 2020; Medeiros et al., 2022; Arango-Castillo et al., 2023)

European (20), North American (15), South American (7), Asian and Oceania (16), and African (18) + global factors as predictors.

New methods on tail risk measurement (see Medeiros et al., 2021, 2022; Goulet Coulombe et al., 2022; Clark et al., 2022)

Quantile random forest provides superior forecasting ability.

Inflation risk measures (see Lopez-Salido and Loria, 2022; Garratt and Petrella, 2022)

I am able to derive inflation risk measures – namely, the probability of high and low inflation – across regions.

Main findings

1. Using global factors, I provide novel framework to measure inflation risk measures across regions.
2. I present further evidence that random forests improve inflation density forecasts.
3. I derive inflation risk measures, that is, the probability of high and low inflation, across regions.
4. I find that global factors are generally robust predictors of density forecasts across countries

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Data

1. **Inflation rates.** I draw primarily on the large global inflation database in Ha et al. (2021) (N=75,T=1980-2021).

2. **Global and regional inflation factors.** To account for the mix of stationary and non-stationary inflation rates, I use the approach developed by Hamilton and Xi (2023)

3. **Real global economic factor.** To control for supply-side fluctuations, I consider a real global economic factor based on commodity prices (see Alquist et al., 2020).

4. **Oil prices and global financial conditions.**

Methodology

- To characterize the τ-quantile of the distribution of future inflation $\pi^h_{i,t+h}$ on a d-dimension vector X_{it} of predictors, I consider the following general model:

$$\pi^h_{i,t+h} = Q_{h,\tau}(X_{i,t}) + u_{i,t},$$

where $Q_{h,\tau}(.)$ is the target quantile function that relates covariates and the distribution of future inflation; and $u_{i,t}$ is an zero-mean $i.i.d$ error term.

Methodology

- The forecast equation is given by

$$\widehat{Q}_{t+h|t,\tau}(\pi^h_{i,t+h}|X_{i,t}) = \widehat{Q}_{t-R_h+1:t,\tau}(X_{i,t}),$$

  where $\widehat{Q}_{t+h|t,\tau}(\pi^h_{i,t+h}|X_{i,t})$ is an estimate of the future quantile function of $\pi^h_{i,t+h}$ for $\tau = \{0.05, 0.25, 0.50, 0.75, 0.95\}$ conditional on the data observed from $t - R_h + 1$ to t, where R_h is the window size.
- Forecasts are based on a rolling-window framework in line with Medeiros et al. (2021, 2022).

Methodology

- Then, a skew-t distribution is fitted.
- The conditional probability that the *h*-step-ahead inflation conditional on $X_{i,t}$ is greater than certain threshold π^* is,

$$IaR_h = P(\pi^h_{i,t+h} > \pi^* | X_{i,t}),$$

with the probability density,

$$\int_{\pi^*}^{\infty} f(\pi^h_{i,t+h} | X_{i,t}, \widehat{\mu}, \widehat{\sigma}, \widehat{\alpha}, \widehat{v}) d\pi_{i,t+h}.$$

Information sets

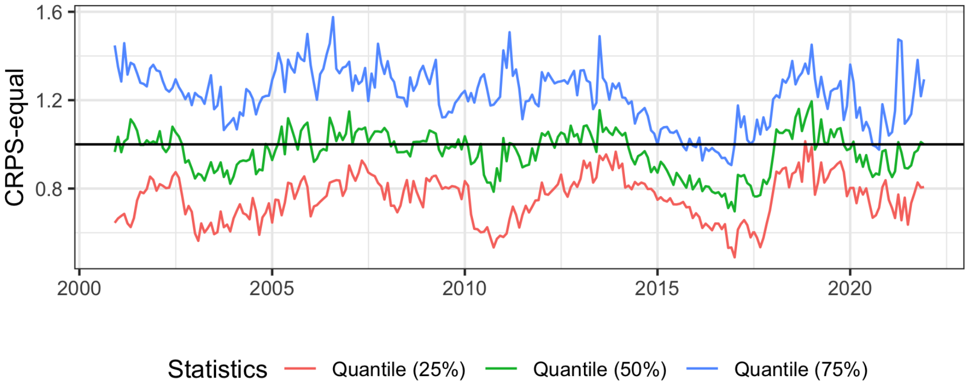
Name	Model	Variable sets
QR-AR	Quantile regression	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}]'$
QR-CM1	Quantile regression	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}, \pi_t^g, \pi_t^r]'$
QR-CM2	Quantile regression	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}, \pi_t^g, \pi_t^r, g_t, oil_t]'$
QR-CM3	Quantile regression	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}, \pi_t^g, \pi_t^r, g_t, oil_t, VIX_t]'$
QRF-AR	Quantile random forest	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}]'$
QRF-CM1	Quantile random forest	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}, \pi_t^g, \pi_t^r]'$
QRF-CM2	Quantile random forest	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}, \pi_t^g, \pi_t^r, g_t, oil_t]'$
QRF-CM3	Quantile random forest	$X_{i,t} = [\{\pi_{i,t-j}\}_{j=o}^{4-1}, \pi_t^g, \pi_t^r, g_t, oil_t, VIX_t]'$

Results

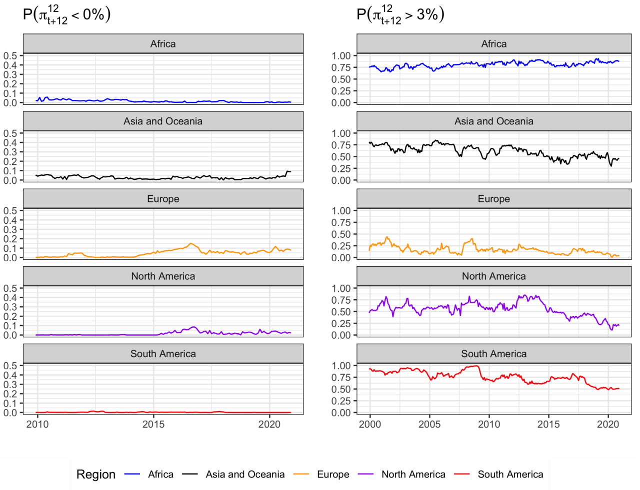
Models	Weighting schemes					DM test		
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Equal	Center	Tails	Right	Left	Equal	Right	left
				$h = 12$				
QR-AR	1.830	0.325	0.529	0.654	0.525	-	-	-
QR-CM1	1.085	1.075	1.111	1.059	1.129	8.0	12.0	9.3
QR-CM2	1.066	1.055	1.093	1.039	1.110	9.3	18.7	9.3
QR-CM3	1.094	1.083	1.122	1.063	1.145	9.3	16.0	5.3
QRF-AR	1.020	1.017	1.029	1.003	1.050	33.3	37.3	20.0
QRF-CM1	0.991	0.992	0.989	0.984	1.000	36.0	40.0	32.0
QRF-CM2	**0.972**	**0.975**	**0.967**	**0.970**	**0.974**	**49.3**	**50.7**	**45.3**
QRF-CM3	0.981	0.985	0.971	0.982	0.977	44.0	44.0	44.0

Where do the cross-sectional gains come from?

Where do the temporal gains come from?



Probability of high and low inflation across world regions (2000-2020)



Chapter 6: Conclusions

Conclusions

This thesis has contributed to our understanding of tail risks in macroeconomics.

- How do US financial conditions impact funding markets (credit and stocks) in a large set of countries around the world under different scenarios of macro-financial distress?
- What role can be played by high-frequency data, real variables, and machine learning techniques in improving the forecasting performance of macroeconomic tail risk measures?
- The study of tail risks in macroeconomics is crucial for international organizations, policy makers, and central banks.
- Looking ahead, I plan to continue exploring tail risks in macroeconomics using machine learning and big data techniques, and studying vulnerable finance episodes.

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Essays on Tail Risks in Macroeconomics

PhD Thesis Defense

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July 14, 2023

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