Risky news

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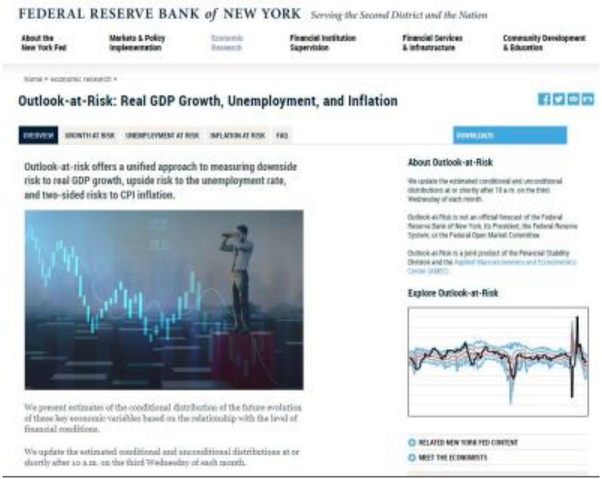
The conditional distribution of GDP growth contains fat tails and skewness (web)



THE STARTING POINT

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Growth-at-risk (GaR): large literature, pioneered by Giglio et al. (2016) and Adrian et al. (2019)

- Defines GaR as the growth rate of output at the 5th percentile
- Maps GaR to indicators of financial stress, e.g., credit, leverage, and funding
  - Commonly used predictor in the U.S.: National Financial Condition Index (NFCI)

Well motivated by economic theory. E.g.:

- Structural models linking financial conditions to business cycles (famous examples Gertler and Bernanke (1989), Kiyotaki and Moore (1997), Bernanke et al. (1999))
- Classic accounts of financial crises emphasizing credit market sentiment (Minsky, 1977, 1986; Kindleberger, 1978)

Thus, provides macro-prudential policies a well grounded framework for managing macro risks (Greenspan (2004)) BUT...

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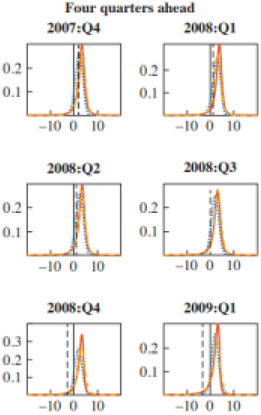
When Is Growth at Risk?

ABSTRACT This paper empirically evaluates the
nexus between financial indicators and the distribution o
using a rich set of macroeconomic and financial variab
advanced economies. We evaluate the out-of-sample f
of financial variables for GDP growth, including a ful
based on a flexible nonparametric model. We also use a
estimate the moments of the time-varying distribution
their in-sample estimation uncertainty. Our overall conc
moments other than the conditional mean are poorly estima
we consider provide robust and precise advance warnings
about any features of the GDP growth distribution oth
particular, financial variables contribute little to such di
beyond the information contained in real indicators.



Conflict of Interest Disclosure: Mikkel Plagborg-Møller is an as
nomics at Princeton University; Lucrezia Reichlin is a professor of
Business School, chair and cofounder of Now-Casting, an adva
monitor macro conditions, a nonexecutive director for the U.K.-ba

CONFLICT

Hasenzagl et al. (2020), henceforth HPRR, have recently convincingly argued that the NFCI (and similar indexes):

- Does only provide predictive power for the location of the conditional distribution of GDP growth (and not any higher order moments)
- Does not contain information beyond what's already in real indicators, such as the first common factor (FMDF) extracted from the commonly used FRED-MD dataset

This is **sad news** for macro-prudential policies and risk management relying on theories linking GaR predictions to financial conditions

Motivated by this debate and its clear policy relevance, we:

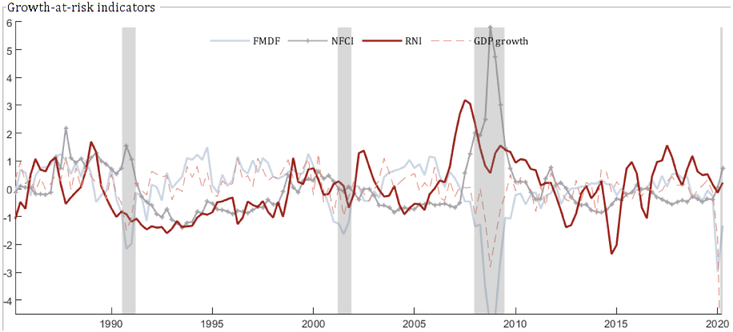
- Propose an alternative new-based indicator, labeled the Risky News Index (RNI), linking financial conditions to growth risks
- Evaluate the proposed indicator in terms of its ability to characterize (in-sample) and predict (out-of-sample) the conditional distribution of U.S. GDP growth
- Dissect the informational content of the derived index by linking it to shocks to expectations about the current state of the economy and popular sentiment-driven views on the credit cycle

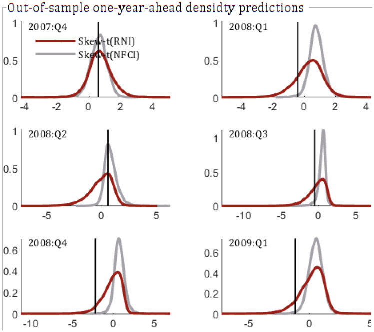
Find that:

- RNI helps characterizing the GDP distribution in-sample and significantly affects the shape of the distribution
- RNI outperforms the NFCI when used for out-of-sample forecasting. Not at the one-quarter-ahead horizon, but significant so at the more policy relevant one-year-ahead horizon

This is **good news** for macro-prudential policies and risk management relying on theories linking GaR predictions to financial conditions.

- Speaking to theories on endogenous information choice and credit-market sentiment we further document that the news-based index carries information about beliefs rather than fundamentals.


Growth-at-risk indicators
FMDF
NFCI
RNI
GDP growth
1990
1995
2000
2005
2010
2015
2020


Out-of-sample one-year-ahead densidty predictions
2007:Q4
Skew-t(RNI)
Skew-t(NFCI)
2008:Q1
2008:Q2
2008:Q3
2008:Q4
2009:Q1

- Constructing the RNI
- Building intuition
- Modeling the conditional distribution of GDP growth
- In- and out-of-sample results
- Economic mechanism

CONSTRUCTING THE RNI

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Use *Dow Jones Newswire Archive* together with a ML based *Word Embedding* model to estimate the association between *growth-at-risk* and *financial conditions*

- Why news:
  - By def. provides the general public with new information (information intermediaries)
  - Might have independent effects on expectation formation via information choice, information rigidities, or more behavioral mechanisms
- Why word embeddings:
  - Vector representation of words capturing linguistic regularities and patterns
  - Allow for arithmetic operations which can capture associative meaning (e.g. *king* - *man* + *woman* $\approx$ *queen*)
  - ChatGPT, and all its new friends, build on this type of data representations
    - Words that share meaning are close in vector space
    - Words that share context are close in vector space

THE DATA

Unique corpus from *Dow Jones Newswire Archive*:

- International business news, e.g., *The Wall Street Journal*
- More than 25 million articles in English language
- We use data from from January 1985 to April 2022
- Perform customary pre-processing

- Estimation method: *word2vec* algorithm, a two-layered neural network (Mikolov et al. (2013) and Mikolov et al. (2013))
- Input:
  - Corpus of Dow Jones Newswire Archive.
  - Partitioned into monthly blocks of articles.
- Output:
  - For each month t, a matrix of word embeddings.
  - For each word, a word vector representing the regularities and patterns of the language (in a particular month).

Defining concepts

$$\begin{aligned} \textit{Growth-at-risk}_t &= (\textit{recession}_t + \textit{risk}_t) \\ \textit{Financial conditions}_t &= (\textit{credit}_t + \textit{leverage}_t + \textit{funding}_t) \end{aligned} \tag{1}$$

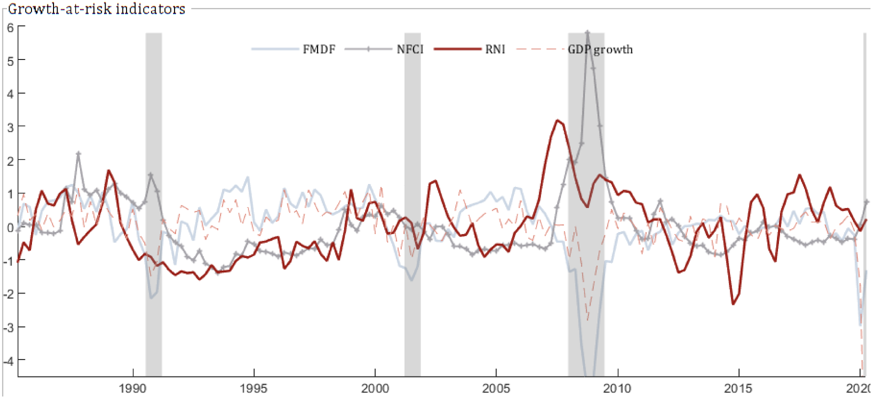
OLS regression (each month)

$$RNI_t \equiv \hat{\beta}_t = \arg\min S(\beta_t) \quad S(\beta_t) = \|\textit{Growth-at-risk}_t - \textit{Financial cond.}_t \times \beta_t\|^2 , \tag{2}$$

Intuition:

- An increase in $RNI_t \equiv \hat{\beta}_t$ implies a stronger association between how the news media writes about growth-at-risk and financial conditions
- To the extent that this reflects changes in economic fundamentals, or if news media coverage has an independent effect on economic expectations, we hypothesis that this change might be informative for characterizing and forecasting skewness and fat tails in GDP growth

THE RNI



Growth-at-risk indicators
FMDF
NFCI
RNI
GDP growth
6
5
4
3
2
1
0
-1
-2
-3
-4
1990
1995
2000
2005
2010
2015
2020

BUILDING INTUITION(?)

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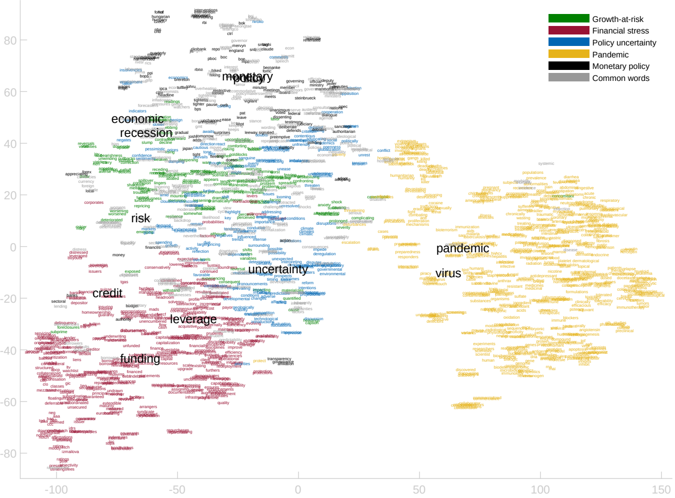

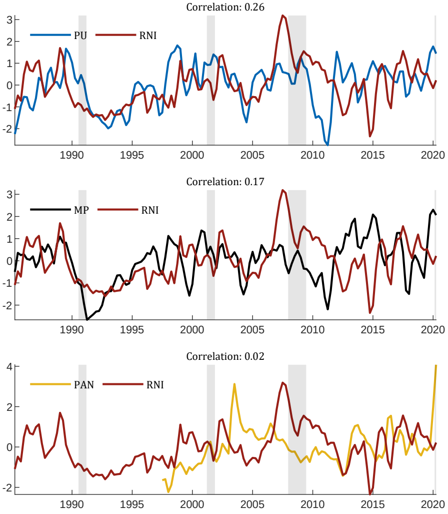

BUILDING INTUITION(?)

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1990

1997

2000

2006

2014

2019

A parametric Skew-t distribution with time-varying location, scale, and shape parameters

- Skew-t workhorse model in the GaR literature
- Score-driven time-varying location, scale, and shape parameters shown to improve performance in newer studies (Labonne (2022) and Delle Monache et al. (2023))

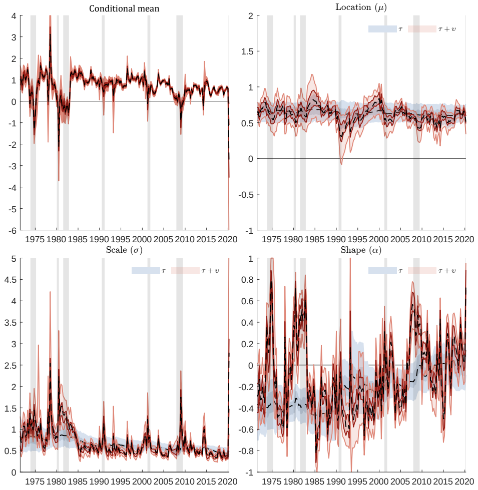
$$y_t = \mu_t + v_t, \quad v_t \sim Skt(0, \sigma_t, \alpha_t, \nu), \tag{3}$$

Letting $\gamma = log(\sigma)$, $\varrho = arcthan(\alpha)$, and $u_t \in \{\mu_t, \gamma_t, \varrho_t\}$, the time-varying parameters have both a stationary and permanent component such that $u_t = \tau_{u,t} + \upsilon_{u,t}$ with

$$\tau_{u,t} = \tau_{u,t-1} + \varsigma_u s_{u,t} \quad \upsilon_{u,t} = \phi_u \upsilon_{u,t-1} + \beta_u x_{t-1} + \kappa_u s_{u,t}, \tag{4}$$

- x an exogenous predictor, e.g., the RNI or NFCI

IN-SAMPLE CHARACTERISTICS



As in Delle Monache et al. (2023) (using a Skew-t(NFCI) model)

- Economic expansions: positive skewness, and positive correlation between the mean and variance of the distribution
- In recessions: negative skewness, and negative correlation between the mean and variance of the distribution

In relation to HPRR:

- They find that financial conditions only explain the location of the distribution and that the time-varying moments are very imprecisely estimated
- We find significant time-variation and that the RNI contributes significantly to the shape (asymmetry), but not the location of the distribution

OUT-OF-SAMPLE PERFORMANCE

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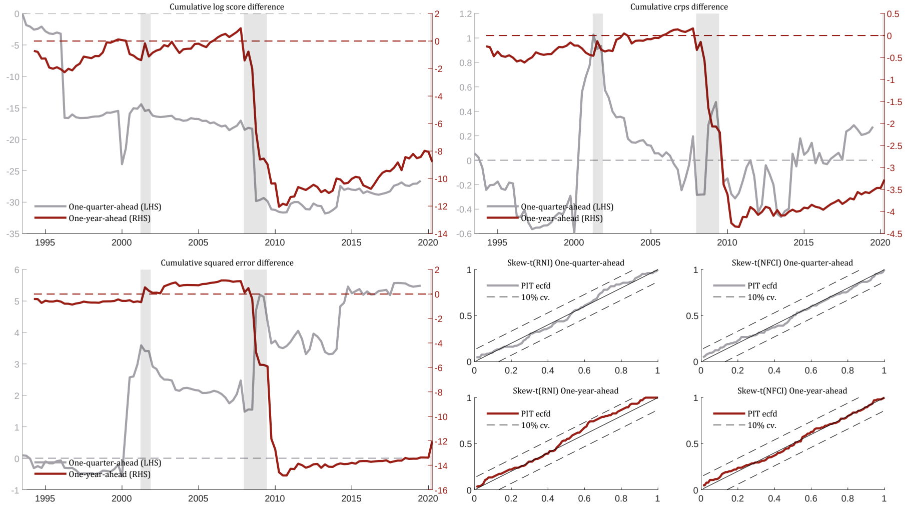

OUT-OF-SAMPLE PERFORMANCE

Table: The table reports the average forecast metrics of the Skew-t(RNI) model relative to the Skew-t(NFCI) model. We use ratios for the RMSE and CRSP, and differences for the LS. Ratios smaller than 1, and positive values of the LS differences indicate that Skew-t(RNI) model performs better than the Skew-t(NFCI) benchmark. The p-value for the Giacomini and White (2006) test are in parentheses.

	One-quarter-ahead			One-year-ahead		
	LS	CRPS	RMSE	LS	CRPS	RMSE
Full	0.06 (0.36)	1.02 (0.55)	1.01 (0.76)	-0.10 (0.44)	0.93 (0.41)	0.91 (0.27)
Rec.	0.15 (0.77)	1.01 (0.95)	1.01 (0.69)	-0.64 (0.13)	0.91 (0.01)	0.94 (0.00)
GFC	0.18 (0.74)	1.11 (0.93)	1.33 (0.73)	-1.10 (0.00)	0.68 (0.00)	0.52 (0.00)

OUT-OF-SAMPLE GAR

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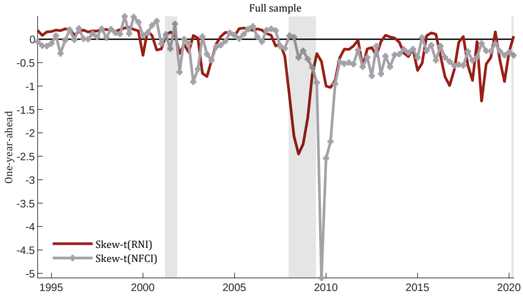
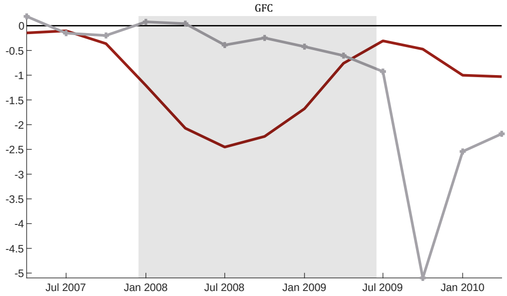
Not only statistical significant results, but also economically significant





IS IT THE METHOD OR THE DATA?

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We show in the paper

- That count-based methods do worse than the word embedding methodology
- That boolean search-based methods do worse than the word embedding methodology
- But, these alternative NLP methods, and in particular the boolean search-based method, do at times perform better than using the NFCI

Thus, seems to be something with the data, i.e., the news!

...the strong performance of the RNI must be related to something else. Given the usage of news data, a natural hypothesis is that we capture fluctuations in beliefs and credit market sentiment (to a larger degree than what's potentially captured by, e.g., the NFCI)

Conduct two main experiments

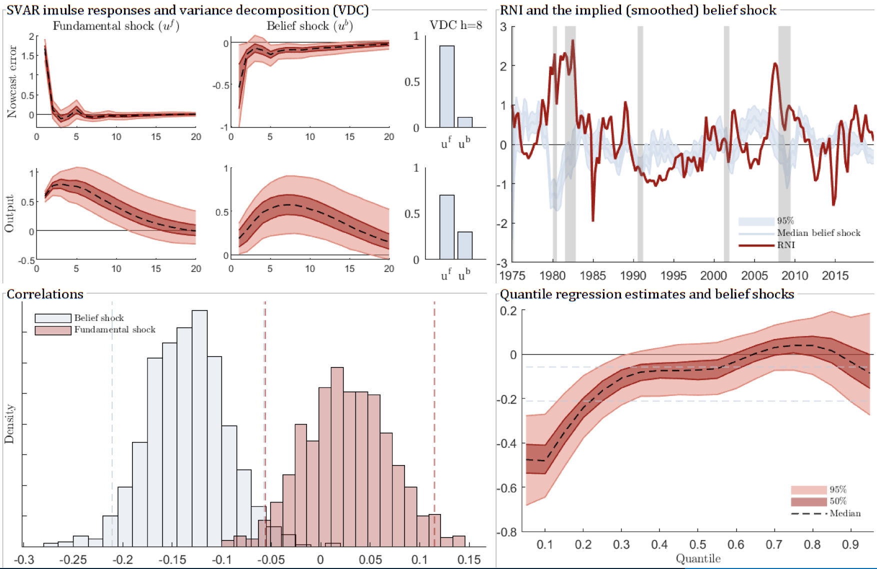
- Bulding on Enders et al. (2021) and Bordalo et al. (2018): Estimate SVAR to identify belief and fundamental shocks using sign restrictions. Look at correlations

$$\begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} = \begin{bmatrix} + & - \\ + & + \end{bmatrix} \begin{bmatrix} u_t^f \\ u_t^b \end{bmatrix} \tag{5}$$

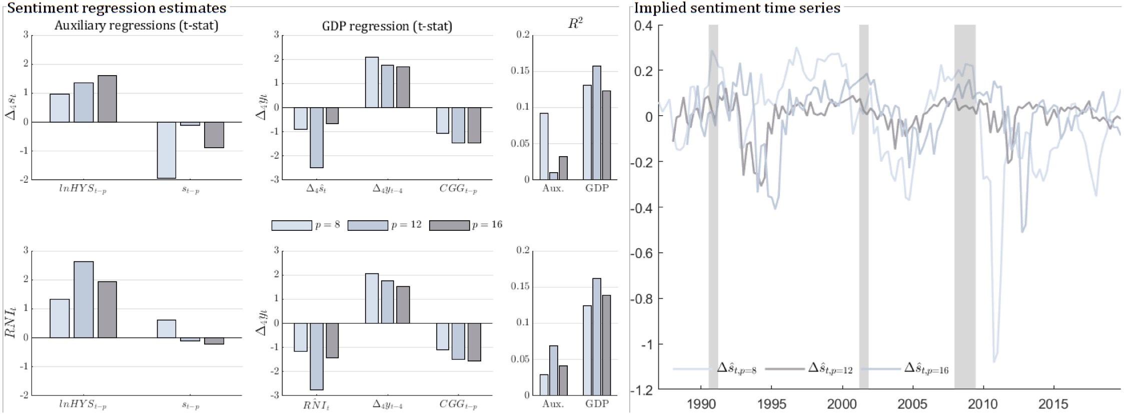
- Build on López-Salido et al. (2017) to identify credit market sentiment via credit market valuation indicators

$$\Delta_4 s_t = \boldsymbol{\theta}' \boldsymbol{z}_{t-p_1} + v_{1,t} \tag{6a}$$
$$\Delta_4 y_t = \beta_1 \Delta_4 \hat{s}_t + \boldsymbol{\gamma}' \boldsymbol{x}_{t-p_2} + v_{2,t}. \tag{6b}$$

RNI SIGNIFICANTLY CORRELATED WITH BELIEF SHOCKS



RNI SIGNIFICANTLY CORRELATED WITH LAGGED VALUATION INDICATORS



CONCLUSION

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- GaR predictions are important policy tools and well grounded in economic theory linking financial conditions to macro outcomes
- HPRR convincingly question the value added of using financial conditions indicators, such as the NFCI, for GaR predictions: **Sad news** for macro-prudential policies and risk management
- We propose an alternative news-based indicator, the RNI, capturing time-varying changes in news coverage of growth-at-risk and financial conditions
  - Using the RNI to characterize the conditional distribution of GDP growth in-sample suggests that financial conditions significantly affect the shape of the distribution
  - Out-of-sample the RNI outperforms the NFCI at the policy relevant one-year-ahead horizon. Our results are both statistically and economically significant: **Good news** for macro-prudential policies and risk management
- More structural experiments relate the RNI to theories on credit market sentiment, and suggest a potential endogenous information choice channel where media coverage matter

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