A Survey-Based Measure of Asymmetric Macroeconomic Risk in the Euro Area

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Motivation: Timely measurement of economic risks

- Macroeconomic risk assessment among main tasks of many economic policy institutions
- Risks often asymmetric around the baseline outlook (‘skewness’)
- Focus mostly on conditional asymmetry of a single economic variable (e.g. GDP growth as in Adrian et al., 2019)
- Iseringhausen, Petrella & Theodoridis (IPT, 2023) develop a data-rich approach to measure ‘aggregate skewness’ in the US economy
    - This paper extends this work along several dimensions

Contribution and preview results

- We construct a factor summarizing asymmetries in risk perceptions
- Based on a large dataset of survey indicators for the euro area
  - Different from IPT (2023): *'soft'* vs. *'hard'* data
- Two empirical applications of (asymmetric) risk measure
  1. Forecasting monthly measures of economic activity
  2. VAR analysis to study the effects of changing risk perceptions
- Main results
  - Asymmetries in risk perceptions change over time
  - Survey-based skewness matters for forecasting and the business cycle

A measure of asymmetric risks: Dataset

- 110 monthly survey series for the EA over 04/2003–12/2023
- Surveys with consumers, businesses, banks, and investors
  - Cover key dimensions of the economy
  - Examples: PMIs, EC Business and Consumer Surveys, ECB Bank Lending Survey (interpolated)
- Popular in private sector and public institutions
  - Short publication lag and small revisions
  - Soft indicators, but e.g. $corr(PMI, GDP_{y/y}) = 0.8$
- Take first differences of each survey series (e.g. Giannone et al., 2008)

Common factor of 'expected skewness' (IPT, 2023)

1. For each (demeaned) variable, estimate an autoregressive quantile model (Engle and Manganelli, 2004) for $\tau = \{0.1, 0.5, 0.9\}$:

$$Q^{\tau}_{i,t} = \beta^{\tau}_{0,i} + \beta^{\tau}_{1,i} Q^{\tau}_{i,t-1} + \beta^{\tau}_{2,i} y_{i,t-1} \mathbb{I}(y_{i,t-1} > 0) + \beta^{\tau}_{3,i} y_{i,t-1} \mathbb{I}(y_{i,t-1} < 0)$$

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2. For each series, compute the expected (Kelley) skewness:

$$\mathbb{E}_t[Skew_{i,t+1}] = \frac{\mathbb{E}_t[Q^{0.9}_{i,t+1}] + \mathbb{E}_t[Q^{0.1}_{i,t+1}] - 2\mathbb{E}_t[Q^{0.5}_{i,t+1}]}{\mathbb{E}_t[Q^{0.9}_{i,t+1}] - \mathbb{E}_t[Q^{0.1}_{i,t+1}]}$$

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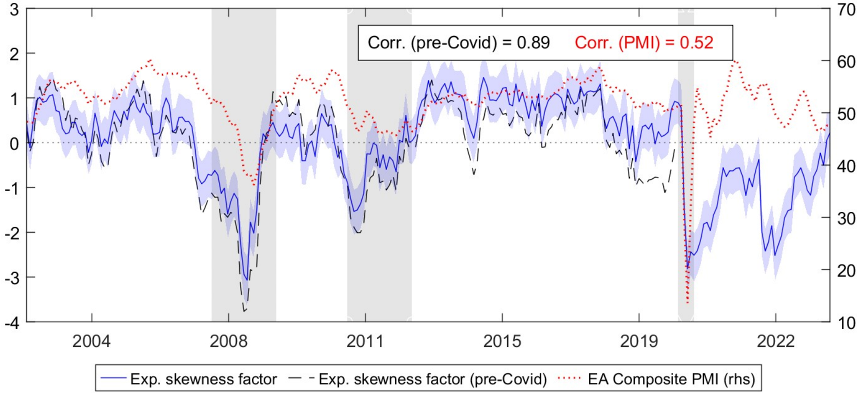
3. Skewness factor is the first PC of individual skewness series ($N = 110$)

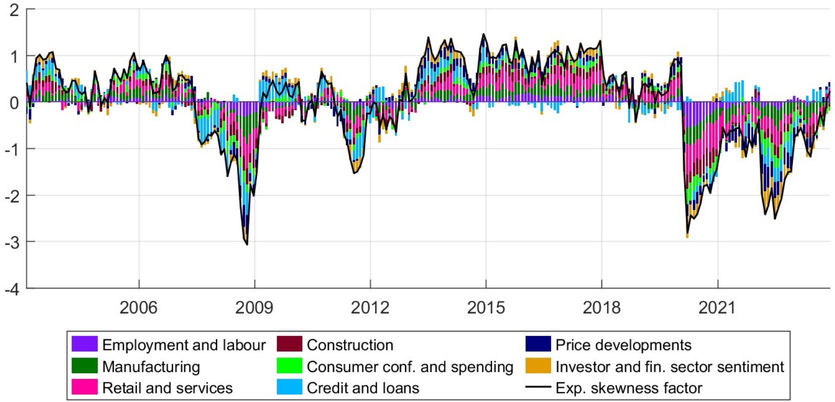
Asymmetries in survey-based risk perceptions



⇒ Expected skewness shifts strongly during times of crisis

⇒ Inclusion of Covid-19 period has limited impact on estimation

Asymmetries in survey-based risk perceptions



⇒ Different groups contribute to exp. skewness at different moments

⇒ Skewness factor is robust to exclusion of any group

Forecasting exercise: Motivation and set-up

- Tradition of forecasting with common factors (Stock and Watson, 2002)
- Value added of higher-moment factors (e.g. skewness)?
- Recursive out-of-sample exercise to forecast economic activity
  - Split into in-sample and out-of-sample period (50%)
  - Forecast different quantiles rather than just cond. mean

$$Q(y)^{\tau}_{t+h} = \gamma^{\tau}_0 + \gamma^{\tau}_1 y_t + \gamma^{\tau}_2 y_{t-1} + \gamma^{\tau}_3 X_t$$

  - $y = \{\text{ind. production, retail sales}\}$, $h = 3$
  - X is either a single survey series (PMI); a common factor of data (PC), exp. volatility (VF), exp. skewness (SF); or a combination of these

Forecasting exercise: Results for retail sales

- Table shows quantile scores for each model and quantile level
- Higher-moment factors can help to improve sales forecasts
  - Volatility factor useful during pre-pandemic sample
  - Skewness factor particularly helpful in full sample

		Quantiles									
		04/2003–12/2019					04/2003–12/2023				
		0.10	*0.25*	*0.50*	*0.75*	*0.90*	*0.10*	*0.25*	*0.50*	*0.75*	*0.90*
I	Benchmark	0.05	0.08	0.09	0.07	**0.03**	0.18	0.24	**0.26**	**0.24**	0.20
II	PMI (svc.)	0.05	0.08	0.09	0.07	0.04	0.18	0.23*	**0.26**	0.25	**0.19**
III	PC	0.05	0.08	0.09	0.07	0.04	0.18	0.23	**0.26**	0.25	0.21
IV	VF	**0.04***	**0.06*****	**0.08*****	**0.06****	**0.03**	0.17	0.23	0.28	0.3	0.25
V	SF	**0.04**	0.07*	0.09	0.07	0.04	**0.16****	**0.22****	0.27	0.27	0.23
VI	PC + SF	**0.04**	0.07	0.09	0.07	0.04	0.17	**0.22***	0.27	0.27	0.22
VII	PC + SF + VF	**0.04**	0.07**	**0.08*****	**0.06****	**0.03**	0.17	0.23	0.28	0.29	0.26

Forecasting exercise: Results for industrial production

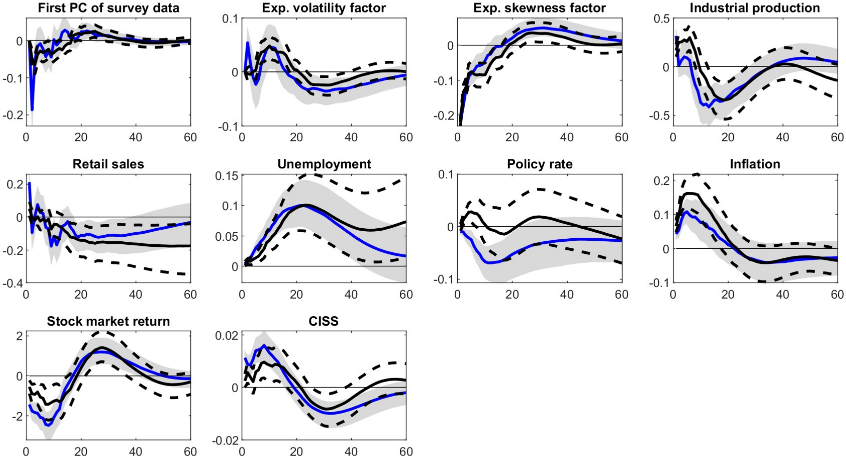
- Results are less pronounced for industrial production
- Still, specifications including skewness factor perform well

		Quantiles									
		04/2003–12/2019					04/2003–12/2023				
		0.10	*0.25*	*0.50*	*0.75*	*0.90*	*0.10*	*0.25*	*0.50*	*0.75*	*0.90*
I	Benchmark	0.11	0.15	**0.16**	**0.12**	0.07	0.28	0.35	**0.36**	**0.31**	0.22
II	PMI (mfg.)	0.11	0.15	**0.16**	**0.12**	**0.06***	0.28	0.35	0.37	**0.31**	0.24
III	PC	**0.09*****	**0.13***	**0.16**	**0.12**	0.07	0.28	0.35	0.37	0.33	0.26
IV	VF	0.10*	0.16	0.17	**0.12**	0.07	0.30	0.39	0.42	0.32	**0.21**
V	SF	0.10**	0.14	**0.16**	**0.12**	0.07	**0.26***	**0.33**	0.38	0.34	0.26
VI	PC + SF	**0.09*****	**0.13****	**0.16**	**0.12**	0.07	0.28	0.34	0.39	0.35	0.26
VII	PC + SF + VF	**0.09****	0.14	0.17	0.13	0.07	0.29	0.37	0.38	**0.31**	0.23

VAR analysis: Motivation and set-up

- Dynamic effects when risk perceptions shift to the downside?
- BVAR model at monthly frequency (04/2003–12/2023)
- Cholesky ordering:
  - [PC(survey data); volatility factor; **skewness factor**; ind. production; retail sales; unemployment; policy rate; inflation; stock market; CISS]
- Exogenous variation in exp. skewness that is orthogonal to contemporaneous changes in the survey data and exp. volatility
- 'Skewness shocks' likely not structural, but reflect linear combination of shocks

VAR analysis: Impulse response functions



Note: The blue solid lines are the posterior median responses to a negative one S.D. shock to survey-based expected skewness along with the 68% highest density intervals. The skewness shock is identified through a Cholesky decomposition. The black lines are the posterior median responses and intervals from a VAR specification with a treatment of the Covid-19 observations (March to August 2020) following Cascaldi-Garcia (2024).

Conclusion

- New measure of (asymmetric) macroeconomic risk for the euro area
  - Combine approach of IPT (2023) with large dataset of survey series
- Expected skewness across survey series comoves strongly during times of crisis, with risk perceptions shifting generally to the downside
- Common factors of higher-order moments (such as skewness) can help improve forecasts of economic activity
  - More work to be done
- Shifts in the perceived balance of risks impact macro-financial outcomes
  - What are the underlying structural shocks driving such shifts?

Appendix

Related literature

1. Tail risks to economic activity and the role of financial conditions (Giglio et al., 2016; Adrian et al., 2019, 2022; Loria et al., 2025; Marfè and Pénasse, 2024)

2. Skewness at the firm and macro level (Jensen et al., 2020; Montes-Galdón and Ortega, 2022; Delle Monache et al., 2024; Iseringhausen et al., 2023; Salgado et al., 2023; Castelnuovo and Mori, 2024; Dew-Becker, 2024; Ferreira, 2024; Iseringhausen, 2024)

3. Measuring (symmetric) uncertainty and its role for the business cycle (Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015; Caggiano et al., 2017, 2021; Carriero et al., 2018; Ludvigson et al., 2021; Miescu and Rossi, 2021; Forni et al., 2024)

4. Modelling comovement of economic variables across their entire cond. distributions (Ando and Bai, 2020; Chen et al., 2021; Korobilis and Schröder, 2024a,b)

5. Forecasting with (non-linear) principal components (Stock and Watson, 2002, 2012; Bai and Ng, 2008; Hauzenberger et al., 2023)

A measure of asymmetric risks: Dataset

- Drop some series (missing obs. or composites), interpolate BLS series
- Judgmentally assign each series to one of eight groups

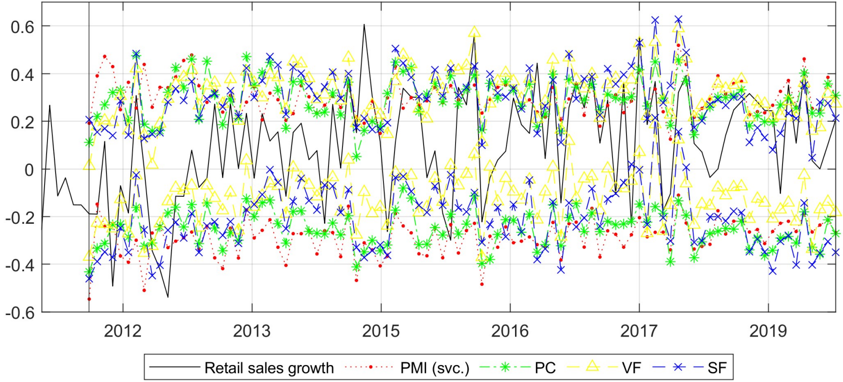
Group	**No.**	**Source**
Employment and labour	13	EC, S&P
Manufacturing	16	EC, S&P
Retail and services	10	EC, S&P
Construction	17	EC, S&P
Consumer confidence and spending	9	EC
Credit and loans	24	ECB
Price developments	13	EC, S&P, ZEW
Investor and financial sector sentiment	8	Sentix, ZEW

Share of variation explained by exp. skewness factor in (%)

Group	No.	Mean	Median	Max.	Min.	Corr. w/o
Retail and services	10	29.0	33.8	55.1	6.0	0.91
Investor and fin. sector sentiment	8	20.4	20.2	49.5	0.0	0.99
Consumer conf. and spending	9	16.4	9.2	53.8	0.2	1.00
Manufacturing	16	14.6	13.3	44.2	0.0	0.98
Price developments	13	14.3	12.6	39.3	3.2	0.99
Construction	17	11.2	6.4	37.4	0.0	0.99
Employment and labour	13	11.1	3.7	41.2	0.3	0.98
Credit and loans	24	5.8	5.3	14.9	0.2	0.96

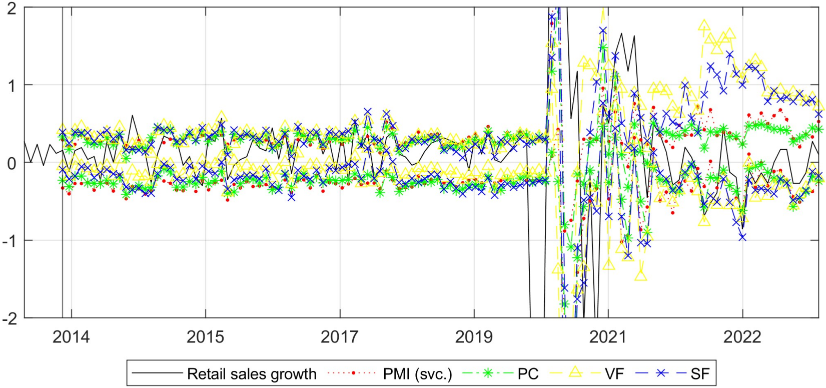
Forecasting exercise: Retail sales (pre-Covid)

⇒ Predicted 10% and 90% quantiles for selected models



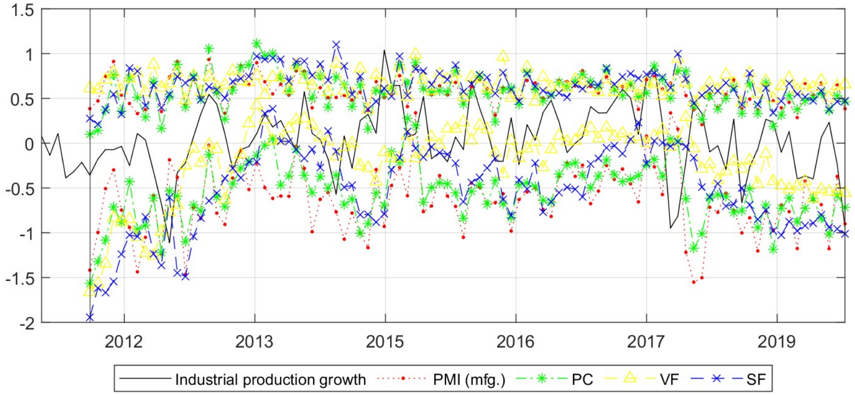
Forecasting exercise: Retail sales (full sample)

⇒ Predicted 10% and 90% quantiles for selected models



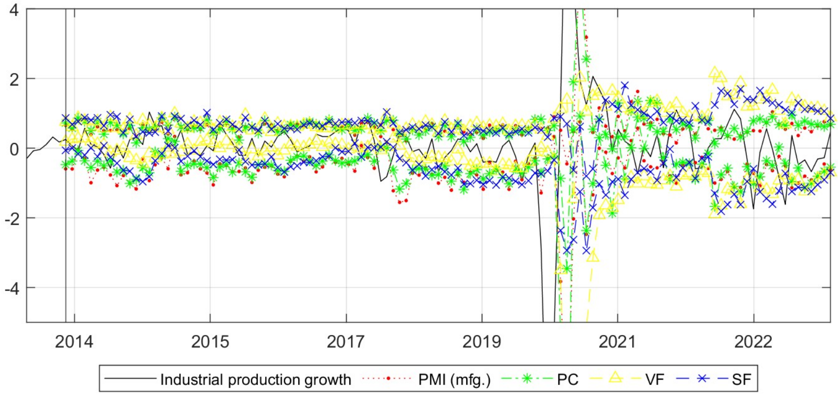
Forecasting exercise: Industrial production (pre-Covid)

$\Rightarrow$ Predicted 10% and 90% quantiles for selected models

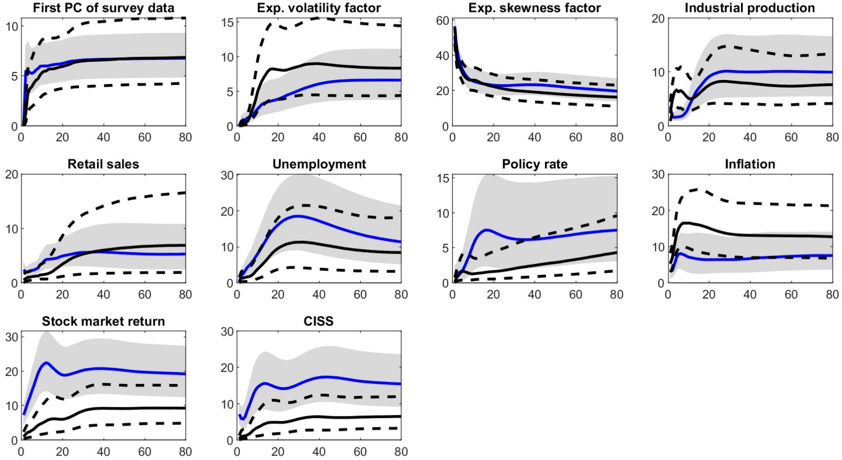


Forecasting exercise: Industrial production (full sample)

⇒ Predicted 10% and 90% quantiles for selected models



VAR analysis: Forecast error variance decompositions



Note: Posterior median of the forecast error variance contributions along with the 68% highest density interval for a shock to survey-based expected skewness.

Robustness checks

- Construction of skewness factor
  - Estimate time-varying quantiles with quantile factor model (Chen et al., 2021) instead of CAViaR model (Engle and Manganelli, 2004)
  - Distinguish between *forward-looking* and *non-forward-looking* survey series
- VAR analysis
  - Alternative ordering of variables
  - Exp. median factor instead of PC(data)
  - Shadow rate (Wu and Xia, 2020) instead of policy rate

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