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

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Abstract

We compute a common factor summarising asymmetries in the expected distributions of a large set of survey-based economic data series for the euro area. This expected skewness factor is distinct from lower-moment factors and can help improve forecasts of risks to economic activity. In addition, within a monthly vector autoregression (VAR), we show that revisions to survey-based expected skewness have macroeconomic and financial implications, even when the average assessment and expected volatility reflected in the surveys remain unchanged. The skewness measure could benefit timely quantitative risk assessments at economic policy institutions to monitor the balance of risks.

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1 Introduction

A timely assessment of both the baseline macroeconomic outlook and prevailing risks are key tasks of many economic policy institutions. Since macroeconomic data are usually published with a sizeable lag, economic analyses are often complemented by studying 'soft' indicators derived from various surveys. Such survey data are usually available during, or shortly after, the reference period and often strongly correlate with actual 'hard' economic data, explaining their popularity in both the public and private sector. Survey-based indicators are regularly used to track the business cycle, but less frequently for the purpose of risk assessment. In this paper, we derive a factor that summarises comovement in expected skewness, i.e. asymmetric risks, using a large dataset of monthly survey-based series for the euro area. In economic terms, we interpret changes in the skewness factor as shifts in the aggregate perceived balance of risks, i.e. the relative importance of downside versus upside risks. We discuss the differences of this skewness measure compared to factors capturing comovement in lower-moment dynamics and illustrate its relevance both in the context of an out-of-sample forecasting exercise and a VAR analysis.

This paper builds on previous work by Iseringhausen et al. (2023), who construct a factor capturing aggregate expected skewness in the US economy based on the FRED-QD (and MD) dataset (McCracken and Ng, 2016, 2020). The authors show that this skewness factor correlates strongly with the cross-sectional skewness of firm-level employment growth (Salgado et al., 2023) and a "Greenbook"-based measure of Fed economists risk assessment (Aruoba and Drechsel, 2024). In addition, Iseringhausen et al. (2023) highlight that revisions in expected skewness give rise to business cycle dynamics fully consistent with the *business cycle anatomy* documented by Angeletos et al. (2020). We extend the analysis of aggregate expected skewness in Iseringhausen et al. (2023) along several dimensions: i) a different geographical area (euro area instead of US), ii) a different type of large dataset (survey-based indicators instead of realised economic outcomes), and iii) additional empirical applications in the form of an out-of-sample forecasting exercise and a modified VAR analysis.

The first part of the paper describes the calculation of the expected skewness factor for the euro area based on a large dataset of survey-based series. We compile a monthly dataset of more than 100 series over the period 2003 to 2023. The data measure the economic sentiment of consumers and sectors such as industry, construction, retail, and services. It also includes information on the assessment of financial market participants and the financial sector. To extract the aggregate expected skewness factor, we apply the approach developed in Iseringhausen et al. (2023). First, estimating univariate autoregressive quantile regressions (Engle and Manganelli, 2004) for each (differenced) survey series, we derive variable-specific series of expected (Kelley) skewness. Second, we obtain the skewness factor as the first principal component from this transformed set of variables, i.e. the set of skewness series computed in the first step. The results show that conditional asymmetries change sharply during times of crisis, with aggregate risks shifting on average to the downside. Moreover, no single group of variables is predominantly driving aggregate dynamics of expected skewness but different groups matter at different points in time. Interestingly, the variables driving the expected skewness factor are often different from those driving comovement in the lower (conditional) moments, i.e. the data itself and expected volatility. Specifically, the series with a relatively high share of skewness variation explained by the common skewness factor are generally not the same ones for which the first principal component of the actual data and a volatility factor have high explanatory power.

In the second part of the paper, we document the relevance of the survey-based expected skewness factor with two empirical applications – an out-of-sample forecasting exercise for monthly measures of economic activity in the euro area and a VAR exercise to study the dynamic impact of revisions in expected skewness, reflecting unexpected changes in the aggregate perceived balance of risks. The out-of-sample forecasting exercise illustrates that factors capturing comovement in higher-order conditional moments, and in particular skewness, can potentially improve forecasts of (risks to) economic activity compared to using a single survey measure or the first principal component of the survey dataset. In addition, the VAR analysis highlights that downward revisions in expected skewness – which are orthogonal to common shifts in the survey data and aggregate expected volatility – can have adverse implications for the macroeconomy and financial markets. The results of the latter empirical application are somewhat more pronounced when including the Covid-19 period in the sample, but remain similar when incorporating a set of time dummies to control for those extreme observations (Cascaldi-Garcia, 2024). Lastly, the results are robust to various alterations of the baseline analysis.

Related literature: Our paper relates to various strands of the literature. First, the general objective of investigating asymmetries in the conditional distribution of survey-based assessments of the economic environment is inspired by a recent literature highlighting tail risks to economic activity, studying their determinants and, in many cases, emphasising a strong link with the evolution of macro-financial conditions (see, for example, Giglio et al., 2016; Adrian et al., 2019, 2022; Marfè and Pénasse, 2024; Loria et al., 2025). Second, and more precisely, our paper builds on a quickly growing literature that strives to measure (conditional) skewness at firm and macro level using different econometric techniques, as well as to understand its importance for business cycle fluctuations and forecasting (Jensen et al., 2020; Montes-Galdón and Ortega, 2022; Iseringhausen et al., 2023; Salgado et al., 2023; Castelnuovo and Mori, 2024; Delle Monache et al., 2024; Dew-Becker, 2024; Ferreira, 2024; Iseringhausen, 2024; Schmitz, 2024). Third, the analysis of skewness dynamics is to some extent a natural progression from the analysis of (symmetric) uncertainty, on which there is a vast literature (see, for example, Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015; Carriero et al., 2018; Ludvigson et al., 2021; Miescu and Rossi, 2021). Cascaldi-Garcia et al. (2023) provide a comprehensive overview. However, already in this literature various contributions have highlighted the importance of asymmetries and state dependence (e.g., Segal et al., 2015; Caggiano et al., 2017, 2021; Andreasen et al., 2024; Forni et al., 2024).

Fourth, our stylised forecasting exercise is motivated by a well-known literature highlighting the potential benefits of using common factors extracted from large datasets for the purpose of forecasting (Stock and Watson, 2002, 2012). To the extent that our skewness factor measures comovement of a non-linear transformation of the data, the paper also links to previous work studying the benefits of non-linear principal component analysis for forecasting (Bai and Ng, 2008; Hauzenberger et al., 2023). Fifth, our VAR analysis relates to previous studies analysing the economic effects of exogenous variation in (consumer) sentiment (see, for example, Barsky and Sims, 2012; Fève and Guay, 2019; Lagerborg et al., 2023). Lastly, while our empirical approach to derive a common factor of expected skewness closely follows Iseringhausen et al. (2023), it relates to a growing strand of the literature aiming at measuring comovement of economic variables not only in the centre of their (conditional) distributions but also in different quantiles (Ando and Bai, 2020; Chen et al., 2021; Ando et al., 2023; Korobilis and Schröder, 2024a,b).

The paper is structured as follows: Section 2 describes the large dataset of survey-based indicators, the empirical approach to derive the expected skewness factor, and the estimation results. Section 3 presents an out-of-sample forecasting exercise and Section 4 the VAR analysis. Section 5 discusses various robustness checks while Section 6 concludes.

2 A survey-based measure of macroeconomic skewness

This section outlines the computation of the expected skewness factor for the euro area. We start by describing the dataset and the empirical approach, where the latter almost exactly follows Iseringhausen et al. (2023), before discussing the results and their interpretation.

2.1 Data

The starting point of our analysis is a set of 140 survey-based indicators for the euro area, covering the period from April 2003 to December 2023. We opted for the use of survey-based data to gauge the state of the economy and the prevailing economic and financial sentiment as most of these series are i) available at a monthly frequency, ii) only published with a small lag, and iii) subject to no or only minor revisions. All of this explains their popularity in policy institutions and the private sector.[1]

The series stem from five different sources and were downloaded from Haver. The largest subsets are the European Commission's Business and Consumer Surveys and the Purchasing Managers' Index series published by S&P, complemented by the ECB's Bank Lending Survey, and surveys among financial experts and investors conducted by Sentix and ZEW.[2] Note that the Bank Lending Survey is conducted quarterly and we interpolate the missing monthly observations using the Denton (1971) method.[3] Before proceeding, we adjust our dataset by dropping i) series that have missing observations over the sample period, and ii) series that are composite measures, usually linear combinations, of other series. This results in a final dataset of $N = 110$ series. Our dataset covers the major dimensions of the economy and we assign each series to one of the following eight groups: *Employment and labour*, *manufacturing*, *retail and services*, *construction*, *consumer confidence and spending*, *credit and loans*, *price developments*, and *investor and financial sector sentiment*. Appendix A and Table A-1 contain details on the data series, including their sources and assignment to groups.

Finally, we follow several papers in the literature and take first differences of all series (see, for example, Giannone et al., 2008; Angelini et al., 2011; Bańbura and Rünstler, 2011; Bańbura et al., 2013). Time series of aggregated survey responses are usually stationary by construction since these are often measured as percentage balances, e.g. the difference between the share of respondents reporting an improvement in economic conditions and the share of respondents reporting a deterioration. However, they can be very persistent: The augmented Dickey and Fuller (1979) test can only reject the null hypothesis of a unit root (at a significance level of 5%) for around 30% of the series.

[1]There is a large literature studying to what extent agents' assessments and expectations reflected in survey data are systematically biased and its economic implications (see, for example, Coibion and Gorodnichenko, 2012; Bordalo et al., 2020; Bhandari et al., 2024). These points are beyond the scope of this paper.

[2]All Business and Consumer Surveys and PMI series (with the exception of *PMI: Services Future Activity*) are provided in seasonally-adjusted terms, while the survey series by Sentix and ZEW, as well as the BLS, are not seasonally adjusted.

[3]For the interpolation, we use growth rates of different credit aggregates (in real terms) as the auxiliary higher-frequency (monthly) indicators. See Appendix A for details.

2.2 Empirical approach

Based on the dataset outlined in the previous section, we compute the common factor of expected skewness following Iseringhausen et al. (2023). We limit the presentation here to a short overview and refer to Iseringhausen et al. (2023) for a more detailed presentation of the approach, including a Monte Carlo simulation exercise (see their online appendix).

The authors develop a simple approach based on combining (univariate) quantile regressions (Koenker and Bassett, 1978) and principal component analysis. After demeaning the data, the first step consists of estimating an *asymmetric slope* autoregressive quantile specification for $\tau = \{0.1, 0.5, 0.9\}$ following Engle and Manganelli (2004) for each of the $N = 110$ survey series:

$$Q^{\tau}_{i,t} = \beta^{\tau}_{0,i} + \beta^{\tau}_{1,i} Q^{\tau}_{i,t-1} + \beta^{\tau}_{2,i} y_{i,t-1} \mathbb{I}(y_{i,t-1} > 0) + \beta^{\tau}_{3,i} y_{i,t-1} \mathbb{I}(y_{i,t-1} < 0), \quad 0 < \beta^{\tau}_{1,i} < 0.95, \quad (1)$$

where $Q^{\tau}_{i,t}$ is the conditional τ-quantile of series i in month t, with $i = 1, ..., N$ and $t = 2, ..., T$.[4] Subsequently, the estimated coefficients from this model are used to compute, for each survey series, the one-month-ahead expected Kelley (1947) skewness:

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

At this point we have obtained a non-linear transformation of the original dataset, consisting of the series-specific Kelley skewness series. In many cases the latter contain a large amount of idiosyncratic noise and we proceed by extracting a common signal from these skewness series. Specifically, the expected skewness factor is obtained as the first principal component of the standardised skewness series. As is well-known for principal component analysis, the sign and scale of the factors are not identified. We identify the scale of the skewness factor by normalising it to have unit variance, while the sign is identified by imposing a positive correlation with economic activity, i.e. the growth rate of euro area industrial production.[5]

[4] Iseringhausen et al. (2023) set the upper bound for the persistence parameter to 0.8. Here, we apply an even looser restriction, but the results are in general not very sensitive to this choice. In addition, in a very small number of cases (less than 0.05% of total observations), there is the issue of crossing quantiles. We address this by sorting the quantiles (Chernozhukov et al., 2010), but this has virtually no impact on the subsequent results.

[5] At various points in the paper, we also refer to an (expected) volatility factor. Similarly to the skewness factor, the volatility factor is also derived based on Equation (1). In particular, it reflects the first principal component of the standardised set of one-step-ahead expected interquartile ranges computed as:

$$\mathbb{E}_t[Vola_{i,t+1}] = \mathbb{E}_t[Q^{0.75}_{i,t+1}] - \mathbb{E}_t[Q^{0.25}_{i,t+1}].$$

The variance of the volatility factor is normalised to one and the scale is identified by assuming a negative correlation with economic activity.

As a final remark, while we focus on studying one-step-ahead – in our case one-month-ahead – expected skewness, adjusting Equations (1) and (2) to a multi-step-ahead framework is straightforward. Similar to Adrian et al. (2022) in the Growth-at-Risk literature, this could provide insights into the term structure of expected skewness. We leave this analysis to future research.

2.3 Results and discussion

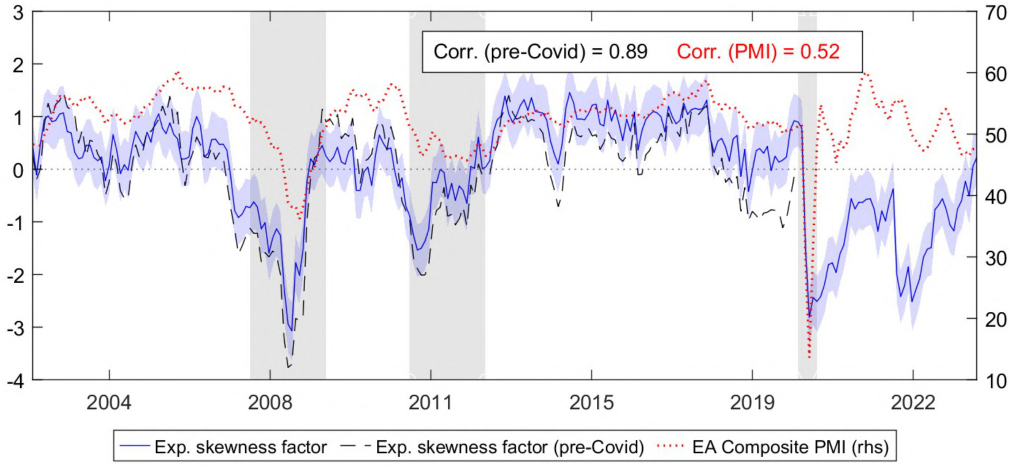
The top panel of Figure 1 shows the survey-based expected skewness factor for the euro area. Similarly to Iseringhausen et al. (2023), we observe that the skewness factor changes more rapidly during times of crisis while expected skewness is relatively stable during more tranquil periods. Shifts in skewness were particularly pronounced during the Global Financial Crisis (GFC, 2007–09) and at the onset of the Covid-19 period (early-2020), but also during the European sovereign debt crisis (2010–12) and around Russia's invasion of Ukraine (early-2022). Figure 1(a) also suggests that shifts in the aggregate balance of risks extracted from survey data in some cases lead economic downturns as measured by the euro area composite PMI, which is one of the most frequently tracked survey series by market participants and policy institutions. Lastly, the skewness factor is largely unaffected by including the (post-)pandemic period in the estimation (see also Iseringhausen et al., 2023).

The seminal paper of Adrian et al. (2019) (ABG) brought the stylised fact of conditional asymmetries in the macroeconomy into the focus of the literature and policymakers. Comparing our skewness factor to a measure of asymmetric risks based on an approach along their lines is thus a natural step (see also Iseringhausen et al., 2023). Figure B-1 in Appendix B presents this comparison, where the *ABG skewness* reflects the expected asymmetry in the predictive distribution of economic activity (proxied by euro area industrial production), conditional on the PMI (manufacturing) and financial stress as measured by the ECB's CISS index (Hollo et al., 2012). Both measures generally comove, but also feature certain differences, with the skewness factor falling more abruptly during the GFC and the onset of the Covid-19 period, while subsequently increasing less.

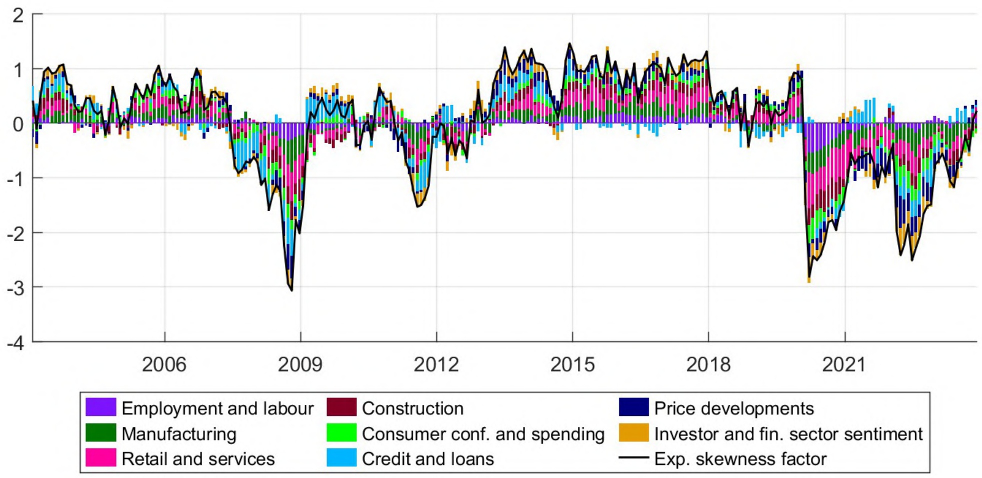
It is also informative to analyse which groups of survey series are mainly driving the aggregate dynamics of the skewness factor. The bottom panel of Figure 1 provides such a decomposition. While all groups of variables contribute to movements in expected skewness at different points in time, some results are worth highlighting. For example, changes in the expected skewness of credit-related series (i.e. the BLS) seem to matter more for overall skewness in the first half of the sample. More recently, changes in the expected asymmetry of survey series related to labour markets, retail and services, but also price developments and financial market/sector perceptions seem to have gained importance as drivers of the skewness factor.

Figure 1: Survey-based skewness factor

(a) First principal component of exp. skewness



(b) Contributions by groups of variables



Note: Figure 1(a) shows the expected skewness factor, both estimated over the full sample and a subsample ending in Dec. 2019, as well as the euro area composite PMI. The blue shaded areas are the bootstrapped confidence bands (90%) around the skewness factor based on Gonçalves and Perron (2020). Gray areas are recessions as dated by the EABCN. Figure 1(b) shows the contributions of the different groups of variables (see Appendix A for details) to the dynamics of the skewness factor.

Table 1, which follows Iseringhausen et al. (2023) in its structure, complements these results by showing that omitting any of the groups does not strongly alter the skewness factor (last column). However, the factor has on average the strongest explanatory power for the expected asymmetry of survey series belonging to the groups retail and services, and investor and financial sector sentiment.

Table 1: Share of variation explained by exp. skewness factor across groups of variables (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

Note: This table presents descriptive statistics for the shares of variation of the individual skewness series explained by the skewness factor (in %). The last column contains the correlation between the skewness factor and an alternative skewness factor obtained from the original dataset but where the variables of the respective group were omitted.

Next, we compare the dynamics of the skewness factor with those of lower-moment factors, i.e. the first principal component of the data (Figure B-2 in Appendix B), and an expected volatility factor (Figure B-3). The latter reflects the first principal component of the set of expected interquartile ranges (see Footnote 5). Comparing the different factors extracted from (non-linear transformations of) our large dataset of survey series can be informative to assess the extent to which conditional higher moments, in particular expected skewness, contain additional information. The upper part of Table 2 illustrates that the comovement between the expected skewness factor and the first principal component of the data was stronger before the Covid-19 period, and declined afterwards. By contrast, the comovement between the expected volatility and skewness factors was sizeable over both periods. Moreover, the skewness factor comoves to some extent with common measures of uncertainty and, especially, financial stress (see Table 2).

Table 2: Correlations of (higher-order moment) factors and shares of variation explained

Corr. of survey-based (higher-order) factors

	04/2003–12/2019			**04/2003–12/2023**		
	PC	VF	SF	PC	VF	SF
PC	1.00	-	-	1.00	-	0.29
VF	-0.48	1.00	-	-0.36	1.00	0.29
SF	0.76	-0.78	1.00	0.29	-0.75	1.00
EPU	-0.16	-0.10	-0.16	-0.18	0.29	-0.38
CISS	-0.35	0.71	-0.65	-0.25	0.32	-0.58
VSTOXX	-0.35	0.78	-0.54	-0.33	0.56	-0.56

Corr. of shares of variation explained by factors

	04/2003–12/2019			**04/2003–12/2023**		
	PC	VF	SF	PC	VF	SF
PC	1.00	-	-	1.00	-	-
VF	0.58	1.00	-	0.80	1.00	-
SF	0.43	0.34	1.00	0.14	0.16	1.00

Avg. share of variation explained by factors (in %)

	19.4	22.5	15.5	25.8	33.8	13.6

Note: The upper part of the table shows the correlations across the first principal components of the data (PC), expected volatility (VF), and expected skewness (SF), respectively, both for the full sample and a subsample ending in Dec. 2019. It also shows the correlations of the principal components with common measures of financial stress and uncertainty: the Economic Policy Uncertainty (EPU) index for Europe constructed by Baker et al. (2016), the euro area (GDP-weighted) Composite Indicator of Systemic Stress (CISS) of Hollo et al. (2012) and the VSTOXX volatility index from STOXX Ltd. The bottom part shows the correlations of the shares of variation explained for each variable by the different principal components (i.e. the correlation matrix of the last three columns in Table B-1 in Appendix B. The table also contains the average share of variation explained by the factors across variables.

The lower part of Table 2 highlights that the three factors – extracted, respectively, from the data, expected volatility, and expected skewness – have explanatory power for different subsets of survey series. In particular, the correlations between the shares of variation explained, i.e. the last three columns of Table B-1 in Appendix B, are often quite small. This is especially true for the skewness factor vis-a-vis the other factors over the full sample, but to a smaller extent also over the pre-pandemic sample. For example, while the correlation between the expected skewness factor and the expected volatility factor over the full sample is around -0.8, the correlation between the respective shares of variation explained across all series, is smaller than 0.2. This is another piece of evidence that the information contained in the dynamics of aggregate conditional higher-order moments, in particular skewness, is potentially different from those contained in lower-order ones. The bottom of Table 2 indicates that the skewness factor can explain, on average, around 14% (16%) of variation in expected skewness across series for the full (pre-Covid) sample, while for the principal components of the data and expected volatility these values stand at 26% (19%) and 34% (23%).[6] As such, comovement in expected skewness appears to have slightly decreased during the pandemic, while both comovement of the data and expected volatility increased.

So far we have not discussed to what extent the skewness factor can be given a more 'directional' interpretation, i.e. are downward movements of the factor generally reflecting that aggregate risk perceptions move to the downside? Inspecting solely Figure 1(a) will not be sufficient to make such statements. Since the signs of principal components and the associated loadings are not separately identified, both components need to be considered jointly in order to map changes in the expected skewness factor back to the individual series-specific skewness dynamics. Specifically, to assess whether the balance of risks of a variable shifts to the upside or downside as the skewness factor moves up or down, one needs to consider the signs of the factor loadings. For each variable, these are reported in Table B-1 in Appendix B. Let us consider a few examples of survey series that correlate particularly strongly with monthly measures of economic activity (see Table B-1), such as *Industry: Production Expectations*, *Consumer: Major Purchases at Present*, *PMI: Services New Export Orders*, and *Euro area: Industry Labor Hoarding*. For these series, the signs of the skewness factor loadings, being

[6]Even though we focus on the first principal component of expected skewness, also the subsequent ones have meaningful explanatory power, e.g. the second principal component accounts for 11% (10%) of variation in the full (pre-Covid) sample.

positive (negative) for the first three (last) series, are such that a drop of the skewness factor reflects a shift of perceived risks to the downside. However, there are other cases, for example *Services: Expected Demand Over Next 3 Months* or *PMI: Manufacturing New Orders*, where the signs of the expected skewness factor loadings are opposite of what one could expect at first glance, i.e. the expected skewness of these series increases as the skewness factor falls. While we would conclude that downward movements of the expected skewness factor shown in Figure 1 are overall associated with perceived risks moving to the downside, this is not necessarily true for each individual survey-based series in our dataset.

3 Forecasting economic activity with survey-based risk measures

This section presents a relatively simple recursive out-of-sample exercise that highlights the usefulness of our survey-based expected skewness factor in forecasting the predictive distribution of monthly measures of economic activity. Specifically, we predict the (average) month-over-month growth rate of both industrial production (IP) and retail sales (RS). Since factors summarising comovement in conditional higher-order moments, including skewness, may be particularly useful for forecasting the tails of the predictive IP/RS growth distribution, we forecast selected quantiles of the dependent variables. Equation (3) shows the general linear quantile model we employ for the out-of-sample forecasting exercise:

$$Q(y)^{\tau}_{t+h} = \gamma^{\tau}_0 + \gamma^{\tau}_1 y_t + \gamma^{\tau}_2 y_{t-1} + \gamma^{\tau}_3 X_t, \tag{3}$$

where $y = \{IP, RS\}$ and $\tau = \{0.1, 0.25, 0.5, 0.75, 0.9\}$ is the respective quantile. The coefficients are again estimated by minimising the tick loss (Koenker and Bassett, 1978). Current and lagged growth rates of IP/RS are included in all our model specifications, while the vector X_t varies across models. As a benchmark, we consider a model that only includes current and lagged growth rates (model I), that is Equation (3) and dropping X_t. Moreover, we include six model specifications with different choices for X_t. Model II includes the PMI (in first differences) for the manufacturing sector (when forecasting IP) and services sector (when forecasting RS), two commonly used indicators to track conditions in these sectors. Model III includes instead the first principal component extracted from the full dataset of survey series, whereas models IV and V include the volatility and skewness factor, respectively. Models VI and VII are slightly larger, where the former includes both the first principal component of the data as well as the skewness factor, and the latter includes all three factors.

For the out-of-sample forecasting exercise, we split our sample in the middle. Specifically, we initially use the first half of the sample to estimate the model parameters and then predict the second half in a recursive (extending window) manner. We focus on one-quarter-ahead predictions ($h = 3$) as a short-term horizon relevant for risk analysis and to smooth some of the volatile month-over-month variation in industrial production and retail sales.[7] In particular, we predict the three-month-ahead average month-over-month growth rate of these variables.[8] To understand the impact of the Covid-19 pandemic (see also Ng, 2021), an extremely turbulent period where economic activity moved sharply, we conduct the out-of-sample forecasting exercise both with (full sample) and without (sample from April 2003 to December 2019) this period. This means that for the full (pre-Covid) sample, the last month of the initial training sample is October 2013 (2011), and we recursively generate 120 (96) out-of-sample forecasts for each quantile and model. Table 3 reports the quantile scores for each quantile and model.[9]

While the exercise is not fully real-time in nature since we do not use real-time vintages of the industrial production and retail sales data, we estimate the different principal components recursively, i.e. they are not subject to look-ahead bias. Figure B-4 in Appendix B contrasts the full-sample estimates of the first principal components of the data, the expected volatility series, and the expected skewness series, with their recursively estimated counterparts. The correlation of both is high in all three cases.

[7]This introduces a mismatch of horizons with respect to the computation of the one-month-ahead expected skewness (and volatility) factor (see Equation (2)). However, the skewness factor is based on a large set of survey series, with the underlying questions often referring to different horizons, and also allows for persistent dynamics. Both points imply that our skewness factor could capture risk perceptions more broadly and potentially be useful in predicting risks to economic activity several months ahead.

[8]Table B-2 in Appendix B shows results for $h = 6$, which overall support the conclusions of the baseline analysis.

[9]The quantile score (or tick loss) is defined as:

$$QS_\tau = \frac{1}{T}\sum_{t=1}^{T}(y_{t+h} - Q(y)^\tau_{t+h})(\tau - \mathbb{I}_{\{y_{t+h}<Q(y)^\tau_{t+h}\}}).$$

To avoid the problem of quantile crossing, we follow Chernozhukov et al. (2010) and sort the predicted quantiles to ensure monotonicity before computing the quantile scores.

In summary, Table 3 shows that our survey-based skewness measure can be helpful to predict (lower) quantiles of monthly measures of economic activity. For industrial production growth over the full sample, Model V, that is the model including the skewness factor, is the only model significantly outperforming the benchmark for the 10% quantile.[10] In addition, over the pre-Covid sample, the principal component of the data has significant predictive power, but models including the skewness factor are also often among the best performing models. In the case of retail sales growth, the skewness factor seems to be helpful in predicting the lower quantiles of the predictive distribution in the full sample, while the volatility factor appears to have sizeable explanatory power in the pre-Covid sample.

Table 3: Results of out-of-sample forecasting exercise ($h = 3$)

			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*
Industrial production	*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
Retail sales	*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	0.30	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

Note: This table reports the quantile scores for a selection of (conditional) quantiles and various model specifications. The dependent variable is the (avg.) month-on-month growth rate of industrial production and retail sales, respectively, $h = 3$ months ahead. PC, VF, and SF are, respectively, the first principal component of the data, expected volatility, and expected skewness. Model I is our benchmark model. Quantile scores reported in bold are the lowest ones for a specific quantile. Each model II to VII also includes current and lagged growth of industrial production/retail sales. ***, **, and * indicate that a specific model outperforms the benchmark based on Diebold and Mariano (1995) tests (using Newey and West (1987) standard errors with lag truncation $h - 1$) at the 1%, 5%, and 10% level, respectively.

[10] The benchmark model is nested and the Diebold and Mariano (1995) test can be invalid in this case (e.g. Clark and McCracken, 2001). Following other studies, we nevertheless use this test here due to the complexity of available alternatives.

In general, quantile scores are much larger in the full sample, which is mainly due to the impact of several months at the onset of the Covid-19 period, and less due to increased parameter uncertainty once the Covid-19 period enters the estimation sample.[11] Figures B-5 and B-6 in Appendix B show the out-of-sample quantile forecasts for selected models.

We tested alternative choices for the set-up of the out-of-sample forecasting exercise (detailed results not reported). In particular, we experimented with different splits of the sample into in-sample and out-of-sample periods, and different numbers of lagged growth terms or even dropping those entirely. While the precise results are somewhat sensitive to some of these choices, the main quantitative result – namely, that the survey-based expected skewness factor can in certain cases help to improve (tail) forecasts of monthly measures of economic activity – persists. This result is also in line with previous work showing that common factors extracted from non-linear transformations of the data, such as expected skewness as described by Equations (1) and (2), can be helpful to forecast macroeconomic outcomes (Bai and Ng, 2008; Hauzenberger et al., 2023). Finally, future work with the aim to take a stronger forecasting perspective could also use additional principal components of expected volatility and skewness, beyond the first ones, which constitute the focus of this paper.

4 The dynamic effects of shifts in survey-based skewness

How important are changes in survey-based risk perceptions for macroeconomic dynamics in the euro area? We strive to answer this question within a simple VAR framework and consider exogenous variation in the survey-based expected skewness factor. The objective here is somewhat different from Iseringhausen et al. (2023), who document that the dynamic reaction of the US economy to revisions in expected skewness, extracted from 'hard' economic data, is nearly indistinguishable from the one following a *main business cycle shock* (Angeletos et al., 2020). Specifically, we focus on pure changes in survey-based expected skewness, i.e. exogenous variation in skewness that is (contemporaneously) orthogonal to (co-)movement in the data and its expected volatility. In economic terms, one could interpret this as a shift in the aggregate perceived balance of risks that does neither affect the 'average assessment'

[11] We also conducted the full sample forecasting exercise without further updating the parameter estimates after 12/2019. This did not alter the results meaningfully (not reported).

nor the 'aggregate level of dispersion' within the same period as reflected in the survey data.

The VAR is estimated with monthly data from April 2003 to December 2023 and includes ten variables: industrial production, retail sales, the unemployment rate, the interest (policy) rate, inflation, stock market returns, an indicator of systemic financial market stress (CISS, see Hollo et al., 2012), as well as the three first principal components obtained, respectively, from the actual dataset of survey series, the set of expected volatility series, and the set of expected skewness series. Equation (4) shows the (reduced-form) VAR representation:

$$y_t = \Theta_0 + \sum_{p=1}^{P} \Theta_p y_{t-p} + u_t, \quad u_t \sim \mathcal{N}(\mathbf{0}, \Sigma), \tag{4}$$

with coefficient matrices Θ_p, a vector of constants Θ_0 and reduced-form disturbances u. The (Bayesian) estimation of this model relies on a Gibbs sampling algorithm and a Minnesota-type prior (Doan et al., 1984; Litterman, 1986; Bańbura et al., 2010; Mumtaz and Zanetti, 2012). Both are relatively standard and akin to Iseringhausen et al. (2023) with further details provided in that reference and their online appendix. We estimate the monthly VAR with $P = 12$ lags and set the shrinkage parameter to $\lambda = 0.25$, which is similar to the values put forward in Bańbura et al. (2010), however, for a dataset with a time dimension twice as long as ours.

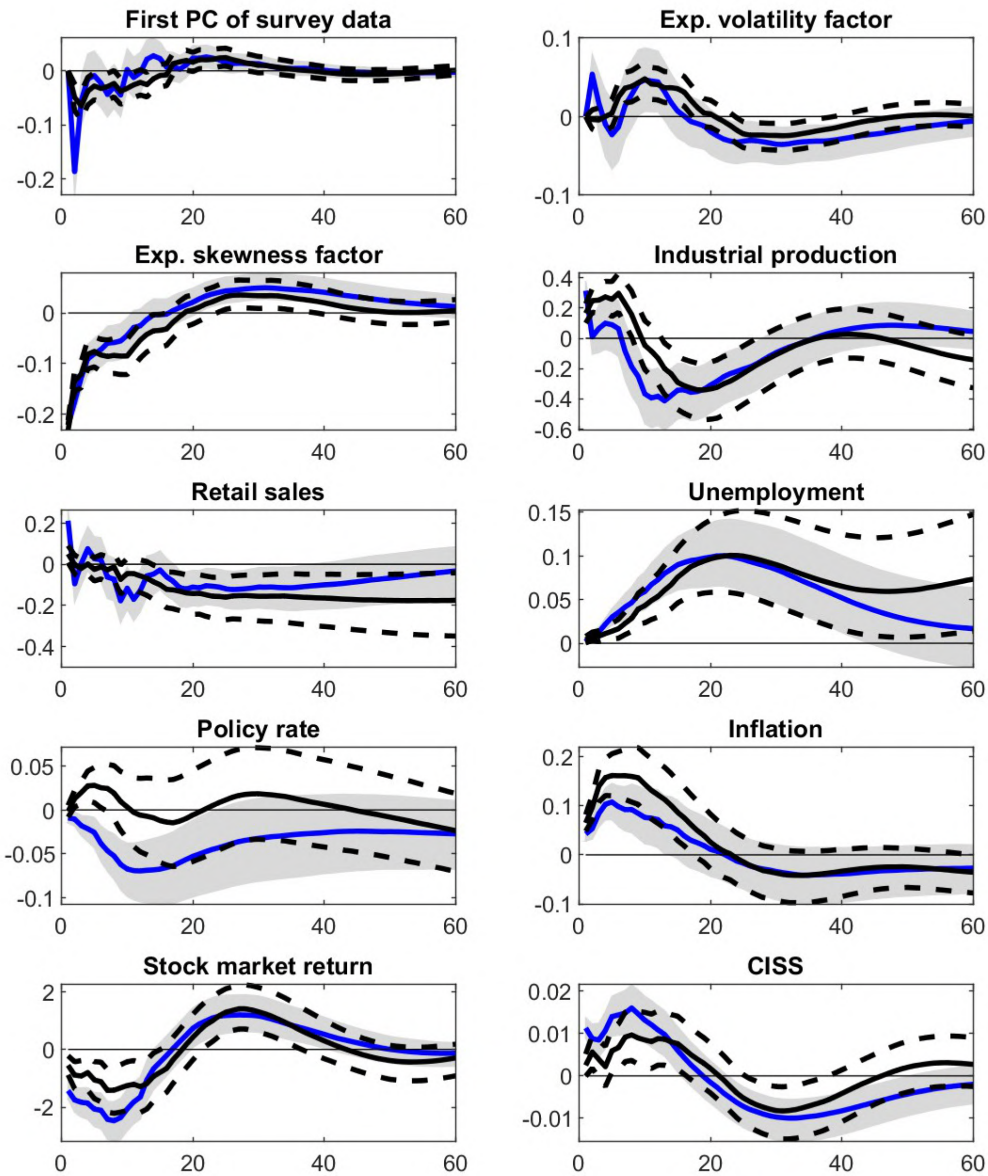
The results of VAR models can be strongly affected by including the Covid-19 period with its extreme observations for several macroeconomic variables, in the estimation sample (Ng, 2021; Lenza and Primiceri, 2022; Carriero et al., 2024; Cascaldi-Garcia, 2024). While our baseline specification does not involve a specific treatment of this period, we also present results when addressing the issue using the approach proposed in Cascaldi-Garcia (2024). The latter extends the prior specification of Bańbura et al. (2010) by a set of time dummies for the period from March to August 2020, and optimally selects the amount of signal taken from those months.

To identify exogenous shifts in expected skewness, we follow Iseringhausen et al. (2023) and use a recursive (Cholesky) scheme, imposing zero restrictions on the matrix of contemporaneous impulse responses. Hence, the latter is the lower triangular matrix resulting from a Cholesky decomposition of the reduced-form error covariance matrix Σ. We order the expected skewness factor third, after the first principal component of the data and the expected volatility factor. This identifies revisions in expected skewness that are orthogonal to contemporaneous changes in the common factors of the data and expected volatilities. We highlight that the 'skewness shocks' identified based on this purely statistical approach are likely not of structural nature, but reflect a linear combination of such shocks (see also Iseringhausen et al., 2023).

Figures 2 and 3 show the impulse response functions to a negative one-standard-deviation shock to survey-based expected skewness, both for our baseline specification and when controlling for the Covid-19 period. Starting with the baseline results, an unexpected negative change in the skewness factor – that is orthogonal to changes in the lower-moment factors – has adverse effects on the economy and financial markets (Figure 2). Measures of economic activity (industrial production and retail sales) fall, unemployment rises, inflation increases, equity prices fall and financial market stress increases. While we are agnostic about the structural nature of the identified survey-based 'skewness shock', these responses are overall consistent with those to a consumer sentiment shock as identified in Lagerborg et al. (2023), who use fatalities in mass shootings as an instrument to identify variation in US consumer sentiment that is unrelated to fundamentals. Moreover, the increase in inflation is consistent with the idea that firms may increase prices in the face of financial frictions and deteriorating demand to maintain liquidity (Gilchrist et al., 2017).[12] Salgado et al. (2023) conduct a similar exercise to ours within a structural macroeconomic model. They find that a one-standard-deviation change in the skewness of firms' productivity shocks – that leaves the mean and variance of the stochastic productivity process unchanged – results in a GDP decline of around 0.4% after four quarters. This is quantitatively similar, both in terms of magnitude and timing, to our baseline results for industrial production. The forecast error variance contributions of the skewness shock (Figure 3) are quite sizeable given that we analyse a pure third-moment shock that has no contemporaneous impact on aggregate movements in the data and expected volatility.

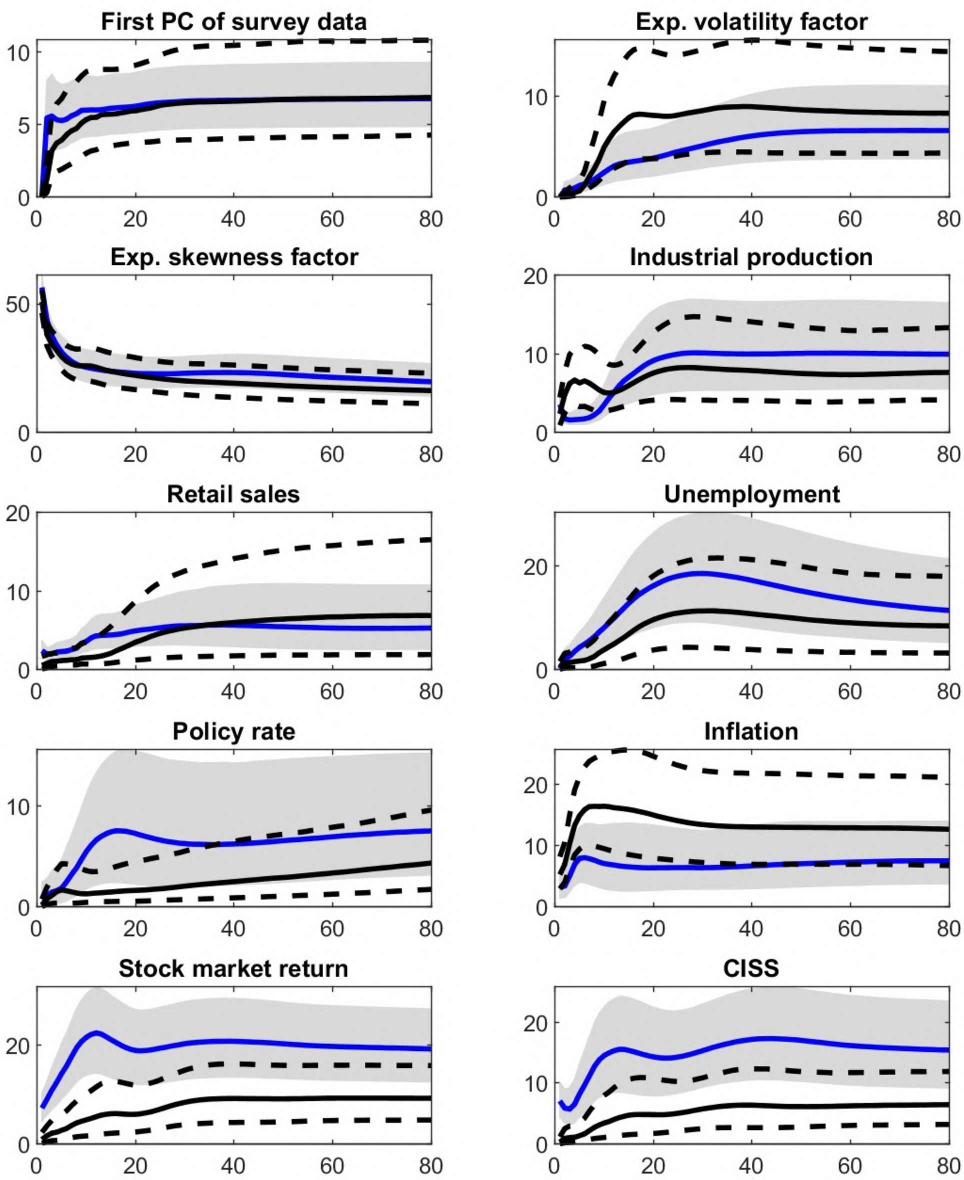
[12] On the consumer side, Kamdar and Ray (2024) highlight that sentiment is more responsive to aggregate supply shocks as these are more costly for most households.

Figure 2: Impulse response functions (baseline model)



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), where the skewness shock is re-scaled to match the magnitude in the baseline model.

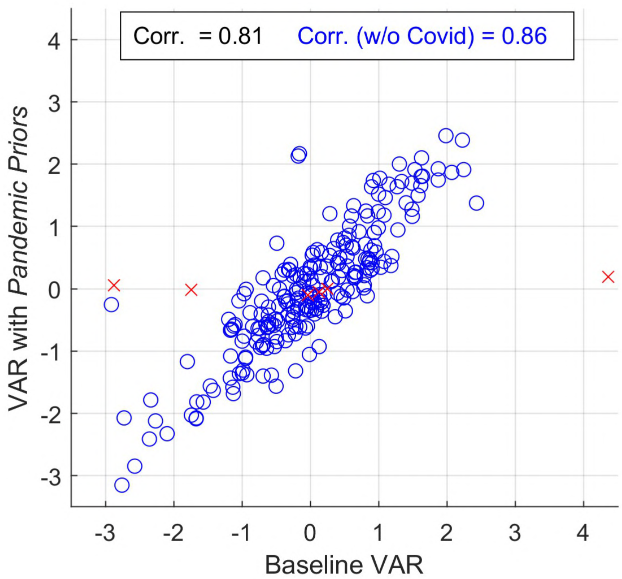
Figure 3: Forecast error variance contributions (baseline model)



Note: Posterior median of the forecast error variance contributions along with the 68% highest density interval for a shock to survey-based expected skewness. See also Figure 2.

When introducing a set of time dummies for the period from March to August 2020 to control for the impact of the extreme observations for some variables during the Covid-19 period, the results are qualitatively similar for most variables (Figures 2 and 3). The responses of the financial market variables, i.e. stock market returns and financial stress (CISS), are somewhat weaker, but the posterior density intervals continue to exclude zero. Moreover, industrial production decreases slightly later after initially increasing, while controlling for the first six months of the pandemic period also results in a stronger response of inflation. Cascaldi-Garcia (2024) shows how to optimally select the prior configuration for these dummies. In our application, the time dummies capture most of the variation in the Covid-19 period, with the optimal hyperparameter being $\phi = 0.075$ (see Cascaldi-Garcia, 2024).

Figure 4: Revisions in expected skewness across VAR specifications



Note: The figure shows the estimated revisions in expected skewness ('skewness shocks') both for the VAR specification with and without a treatment of the observations during the Covid-19 period. The latter follows Cascaldi-Garcia (2024) and the red crosses indicate the Covid-19 observations (March to August 2020). The reported correlations reflects the ones of the median shocks computed across all MCMC draws.

While our VAR results remain qualitatively unaffected when controlling for the Covid-19 observations, revisions in expected skewness were large during this period. Figure 4 contrasts the Cholesky-identified skewness shocks obtained from the baseline VAR and the VAR augmented with Covid-19 dummies (Cascaldi-Garcia, 2024). The results show that i) revisions in expected skewness from both specifications are strongly correlated, and ii) revisions in expected skewness were large in some months at the onset of the Covid-19 crisis (red crosses). First, this suggests that controlling for the Covid-19 period does not fundamentally 'distort' the identification of skewness shocks in the remaining sample. Second, the fact that revisions in expected skewness, potentially reflecting sudden adjustments in the aggregate perceived balance of risks, were large when Covid-19 hit, aligns with previous studies that highlight the importance of uncertainty shocks during Covid-19 (Miescu and Rossi, 2021).

In summary, revisions in the survey-based expected skewness factor have real-economy effects. Specifically, we show that such unexpected changes in the aggregate perceived balance of risks matter even when controlling for the 'average assessment' and the 'aggregate level of dispersion' as reflected in the survey data. Section 5 discusses additional alterations of our baseline VAR model to check the robustness of the results presented in this section.

5 Robustness checks

This section presents additional analysis to test the robustness of some of the main results presented in earlier sections along different dimensions. First, we derive the skewness (and volatility) factor using an alternative approach. In particular, we compare our expected skewness factor with an alternative factor, where the first step of estimating the time-varying conditional quantiles, and thus the conditional Kelley skewness for each variable, is based on the quantile factor model of Chen et al. (2021).[13] Their approach extends principal component analysis to the context of quantile regression. Using their methodology (and MATLAB code), we extract three common factors from each of the conditional 10%, 25%, 50%, 75% and 90% quantiles of the data – after flipping the sign of some series to ensure only positive correlations – and compute the fitted quantiles/skewness series using these factors and the respective factor loadings. The skewness (and volatility) factor are then once again derived as the first principal component of the variable-specific Kelley skewness series (interquartile ranges).[14] Figure C-1 in Appendix C shows that the resulting volatility and skewness factors across both approaches share overall similar dynamics.

Second, we distinguish the impact of different survey series on the overall expected skewness factor depending on whether the underlying question to participants has a *forward-*

[13]Relatedly, Iseringhausen et al. (2023) show that using the score-driven model of Delle Monache et al. (2024) to estimate time-varying skewness based on the FRED-QD dataset (McCracken and Ng, 2020) gives rise to a very similar skewness factor.

[14]For these alternative factors we compute two-month moving averages to obtain a somewhat less noisy series.

looking character. To this end, we compute an alternative skewness factor that only relies on survey series that involve questions about expectations or refer to a time horizon in the future (see Table A-1 in Appendix A). Figure C-2 in Appendix C shows our baseline factor together with this alternative skewness factor (which is based on 36/110 series) and a factor using all remaining (non-forward-looking) series (74/110). The overall expected skewness factor is almost identical to the latter, which builds on the majority of series. Nevertheless, also the correlation with the forward-looking factor is sizeable (around 0.65) and the dynamics are similar, although the latter is somewhat more volatile. An interesting difference is, for example, the Covid-19 period, where expected skewness based on survey series related to current or past developments moved sharply, while the one based on forward-looking survey variables did not.

Third, we test the robustness of the VAR results with respect to the ordering of the variables in the recursive identification scheme. Instead of our baseline choice, which identifies a revision in expected skewness that is orthogonal to movements of the first principal components of the data and expected volatility, we order the three factors after the macroeconomic variables, but before the financial variables. This implies contemporaneous orthogonality of a revision in expected skewness with respect to all macroeconomic variables and the lower-moment factors, while the financial variables can still react instantaneously. Figures C-3 and C-4 show that the impulse response functions and the forecast error variance decompositions remain comparable in the baseline specification, but somewhat weaker when including the set of dummies for the Covid-19 period.

Finally, we consider alternative choices of variables in the VAR. We start by replacing the first principal component of the data with an expected median factor, a measure of aggregate movements in centrality that is conceptually aligned with the quantile-based factors of expected volatility and expected skewness.[15] Figures C-5 and C-6 show that in this case the baseline results remain very similar, while the estimation including Covid-19 dummies provides quantitatively somewhat weaker results. In addition, we also estimate the baseline VAR model replacing the policy rate with a so-called shadow rate that accounts for uncon-

[15]The expected median factor is the first principal component of the set of series-specific expected medians based on Equation (1) and standardised to have unit variance. Similarly to the first princical component of the data, we identify the sign of the median factor by imposing a positive correlation with economic activity.

ventional monetary policies (Wu and Xia, 2020). Figures C-7 and C-8 confirm that the results are very similar for both specifications.

6 Conclusion

Survey-based economic indicators are regularly used to track the business cycle in a timely manner, but less regularly so for the purpose of risk assessment. We compute a common factor summarising expected skewness – a concept to characterise asymmetries in the aggregate perceived balance of risks – in the euro area based on more than 100 monthly survey series over the period from 2003 to 2023. Comovement in expected skewness across series increases during times of crisis, with aggregate risks shifting in general to the downside. No single group of variables is predominantly driving aggregate dynamics of expected skewness but different groups matter at different points in time. Finally, dynamics in survey-based aggregate expected skewness differ markedly from factors capturing comovement in lower-moment dynamics.

We illustrate the skewness factor's relevance both through an out-of-sample forecasting exercise and a VAR analysis. The out-of-sample forecasting exercise suggests that factors capturing comovement in conditional higher-order moments, and in particular skewness, can potentially improve forecasts of (risks to) economic activity compared to relying on a single commonly used survey measure or the first principal component of a large set of survey series. Within a monthly VAR model, we highlight that revisions in expected skewness that are orthogonal to comovement in the data and expected volatility can have implications for the macroeconomy and financial markets. The results are robust to various alterations of the baseline analysis. More generally, the survey-based skewness measure proposed in this paper could benefit regular quantitative risk assessments at economic policy institutions.

Future research could extend the analysis in this paper in various directions, including by studying the term structure of expected skewness by moving beyond the one-step-ahead framework or investigating the factor structure of expected skewness in more detail by considering additional principal components. In addition, a more sophisticated identification of 'skewness shocks' and establishing a closer link with the theoretical literature analysing the role of consumers' and firms' optimism and pessimism for business cycle fluctuations (see, for example, Angeletos and La'O, 2013; Angeletos et al., 2018; Bhandari et al., 2024; Kamdar and Ray, 2024) may be promising avenues.

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Appendix A Data

Groups of variables

We assign each of the survey series to one of eight groups (see Table A-1). These groups (and the number of series per group) are:

1. Employment and labour (13)
2. Manufacturing (16)
3. Retail and services (10)
4. Construction (17)
5. Consumer conf. and spending (9)
6. Credit and loans (24)
7. Price developments (13)
8. Investor and fin. sector sentiment (8)

Interpolation of quarterly ECB Bank Lending Survey (BLS)

We interpolate the 'missing' monthly observations of the quarterly BLS series with the Denton (1971) method, using monthly growth rates of different real credit measures as the high-frequency indicator for changes in loan demand. For the series measuring changes in credit standards, we flip the sign of the auxiliary series (since an increase in these BLS series corresponds to a tightening). Specifically, we use the 3-month growth rate of seasonally-adjusted:

- Outstanding MFI loans to non-financial corporations to interpolate BLS series referring to business loans for small/medium and large companies. Source: ECB.
- Outstanding MFI loans to non-financial corporations (with original maturity of up to 1 year) to interpolate BLS series referring to short-term business loans. Source: ECB.
- Outstanding MFI loans to non-financial corporations (with original maturity of over 5 years) to interpolate BLS series referring to long-term business loans. Source: ECB.
- Outstanding MFI loans to households (consumer credit) to interpolate BLS series referring to consumer credit. Source: ECB.
- Outstanding MFI loans to households (lending for house purchases) to interpolate BLS series referring to loans for house purchases. Source: ECB.

To price-adjust the credit aggregates, we use the euro area HICP (PPI industry excl. construction), both obtained from Eurostat, for loans to households (non-financial corporations).

Table A-1: Survey series, sources, grouping, and transformations

Survey series	**Source**	**Unit**	**Group**	**FW**	**Transf.**
Industry: Production Expectations	EC	% Bal.	2	1	FD
Industry: Volume of Order Books	EC	% Bal.	2	0	FD
Industry: Stocks of Finished Products	EC	% Bal.	2	0	FD
Industry: Volume of Export Order Books	EC	% Bal.	2	0	FD
Industry: Selling Price Expectations	EC	% Bal.	7	1	FD
Industry: Production Trend in Recent Months	EC	% Bal.	2	0	FD
Industry: Employment Expectations	EC	% Bal.	1	1	FD
Consumer: Finan Situation last 12 Mo	EC	% Bal.	5	0	FD
Consumer: Finan Situation next 12 Months	EC	% Bal.	5	1	FD
Consumer: Gen Econ Situation next 12 Mo	EC	% Bal.	5	1	FD
Consumer: Major Purchases next 12 Mo	EC	% Bal.	5	1	FD
Consumer: HH Fin Situation: Sample Total	EC	% Bal.	5	0	FD
Consumer: Major Purchases at Present	EC	% Bal.	5	0	FD
Consumer: Savings at Present	EC	% Bal.	5	0	FD
Consumer: Savings over next 12 Months	EC	% Bal.	5	1	FD
Consumer: Gen Econ Situation last 12 Mo	EC	% Bal.	5	0	FD
Consumer: Price Trends last 12 Months	EC	% Bal.	7	0	FD
Consumer: Price Trends next 12 Months	EC	% Bal.	7	1	FD
Consumer: Unempl Expectations next 12 Mo	EC	% Bal.	1	1	FD
Retail: Present Business Situation	EC	% Bal.	3	0	FD
Retail: Volume of Stocks	EC	% Bal.	3	0	FD
Retail: Expected Business Situation	EC	% Bal.	3	1	FD
Retail: Orders Placed with Suppliers	EC	% Bal.	3	0	FD
Retail: Selling Price Expectations	EC	% Bal.	7	1	FD
Retail: Employment Expectations	EC	% Bal.	1	1	FD
Services: Business Development Over Prev 3 Months	EC	% Bal.	3	0	FD
Services: Evolution of Demand Over Prev 3 Months	EC	% Bal.	3	0	FD
Services: Expected Demand Over Next 3 Months	EC	% Bal.	3	1	FD
Services: Evolution of Employment Over Prev 3 Months	EC	% Bal.	1	0	FD
Services: Price Expectations Over Next 3 Months	EC	% Bal.	7	1	FD
Construction: Volume of Order Books	EC	% Bal.	4	0	FD
Construction: Employment Expectations	EC	% Bal.	1	1	FD
Construction: Price Expectations	EC	% Bal.	7	1	FD
Construction: Trend of Activity , Past 3 months	EC	% Bal.	4	0	FD
Constr: Factors Limiting Bldg Activity: Demand	EC	%	4	0	FD
Constr:Limits to Bldg Activity:Weather Conditions	EC	%	4	0	FD
Constr: Limits to Bldg Activity: Labor Shortage	EC	%	1	0	FD
Constr: Limits to Bldg Activity: Eqpt Shortage	EC	%	4	0	FD
Constr: Limits to Bldg Activity: Other Factors	EC	%	4	0	FD
Constr: Limits to Bldg Activity: Fin Constraints	EC	%	4	0	FD
Euro area: Construction Labor Hoarding	EC	%	1	0	FD
Euro area: Industry Labor Hoarding	EC	%	1	0	FD
Euro area: Retail Labor Hoarding	EC	%	1	0	FD
Euro area: Services Labor Hoarding	EC	%	1	0	FD
Economic Sentiment, Current Macroeconomic Conditions	ZEW	% Bal.	8	0	FD
Econ Sentiment, Macroecon Expectations [Next 6 Mos]	ZEW	% Bal.	8	1	FD
Financial Market Survey: Inflation Expectations	ZEW	% Bal.	7	1	FD
Financial Market Survey: S-T Interest Expectations	ZEW	% Bal.	8	1	FD
Financial Market Survey: Stock Mkt Expectations	ZEW	% Bal.	8	1	FD
Inst Investors Economic Expectations/Sentiment	Sentix	% Bal.	8	1	FD
Private Investors Economic Expectations/Sentiment	Sentix	% Bal.	8	1	FD
Inst Investors Economic Index, Current Situation	Sentix	% Bal.	8	0	FD
Private Investors Economic Index, Current Situation	Sentix	% Bal.	8	0	FD
PMI: Manufacturing Output	S&P/HCOB	>50=Exp.	2	0	FD

Table A-1: Survey series, sources, grouping, and transformations

Survey series	**Source**	**Unit**	**Group**	**FW**	**Transf.**
PMI: Manufacturing New Orders	S&P/HCOB	>50=Exp.	2	0	FD
PMI: Manufacturing Employment	S&P/HCOB	>50=Exp.	1	0	FD
PMI: Manufacturing Suppliers' Delivery Times	S&P/HCOB	>50=Contr.	2	0	FD
PMI: Manufacturing Stocks of Purchases	S&P/HCOB	>50=Exp.	2	0	FD
PMI: Manufacturing Input Prices	S&P/HCOB	>50=Exp.	7	0	FD
PMI: Manufacturing Quantity of Purchases	S&P/HCOB	>50=Exp.	2	0	FD
PMI: Manufacturing Stocks of Finished Goods	S&P/HCOB	>50=Exp.	2	0	FD
PMI: Manufacturing New Export Orders	S&P/HCOB	>50=Exp.	2	0	FD
PMI: Manufacturing Output Prices	S&P/HCOB	>50=Exp.	7	0	FD
PMI: Manufacturing Backlogs of Work	S&P/HCOB	>50=Exp.	2	0	FD
PMI: Manufacturing Orders to Inventories	S&P/HCOB	Ratio	2	0	FD
PMI: Services Employment	S&P/HCOB	>50=Exp.	1	0	FD
PMI: Services Prices Charged	S&P/HCOB	>50=Exp.	7	0	FD
PMI: Services New Business	S&P/HCOB	>50=Exp.	3	0	FD
PMI: Services Input Prices	S&P/HCOB	>50=Exp.	7	0	FD
PMI: Services New Export Orders	S&P/HCOB	>50=Exp.	3	0	FD
PMI: Services Future Activity	S&P/HCOB	>50=Exp.	3	1	FD
PMI: Construction Housing Activity	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Commercial Activity	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Civil Engineering Activity	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction New Orders	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Employment	S&P/HCOB	>50=Exp.	1	0	FD
PMI: Construction Quantity of Purchases	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Delivery Times	S&P/HCOB	>50=Contr.	4	0	FD
PMI: Construction Subcontractor Availability	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Subcontractor Usage	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Subcontractor Quality	S&P/HCOB	>50=Exp.	4	0	FD
PMI: Construction Subcontractor Rates	S&P/HCOB	>50=Exp.	7	0	FD
PMI: Construction Input Prices	S&P/HCOB	>50=Exp.	7	0	FD
PMI: Construction Business Expectations	S&P/HCOB	>50=Exp.	4	1	FD
PMI: Manufacturing Capacity Utilization	S&P/HCOB	>50=Exp.	2	0	FD
Productivity: Manufacturing & Services	S&P/HCOB	>50=Impr.	2	0	FD
BLS: Chg in Credit Stds for Bus Lns to Med/Sm Cos, Past 3M	ECB	% Bal.	6	0	FD
BLS: Chg in Credit Stds for Bus Lns to Large Cos Past 3M	ECB	% Bal.	6	0	FD
BLS: Chg in Credit Stds for Short-term Bus Lns, Past 3M	ECB	% Bal.	6	0	FD
BLS: Chg in Credit Stds for Long-term Bus Lns, Past 3M	ECB	% Bal.	6	0	FD
BLS: Chg in Cr Stds, Past 3M, Apprv Cons Cr/Oth Ldg	ECB	% Bal.	6	0	FD
BLS: Chg in Cr Stds, Past 3M, Apprv House Purch Lns	ECB	% Bal.	6	0	FD
BLS: Chg in Credit Stds for Bus Lns to Ned/Sm Cos, Next 3M	ECB	% Bal.	6	1	FD
BLS: Chg in Credit Stds for Bus Lns to Large Cos Next 3M	ECB	% Bal.	6	1	FD
BLS: Chg in Credit Stds for Short-term Bus Lns, Next 3M	ECB	% Bal.	6	1	FD
BLS: Chg in Credit Stds for Long-term Bus Lns, Next 3M	ECB	% Bal.	6	1	FD
BLS: Chg in Cr Stds, Next 3M, Apprv Cons Cr/Oth Ldg	ECB	% Bal.	6	1	FD
BLS: Chg in Cr Stds, Next 3M, Apprv House Purch Lns	ECB	% Bal.	6	1	FD
BLS: Chg in Bus Loan Demand, Past 3M, Med/Small Cos	ECB	% Bal.	6	0	FD
BLS: Chg in Bus Loan Demand, Past 3M, Large Cos	ECB	% Bal.	6	0	FD
BLS: Chg in Bus Loan Demand, Past 3M, Short-term	ECB	% Bal.	6	0	FD
BLS: Chg in Bus Loan Demand, Past 3M, Long-term	ECB	% Bal.	6	0	FD
BLS: Chg in HH Demand for Cons Credit, Past 3M	ECB	% Bal.	6	0	FD
BLS: Chg in HH Demand for Housing Loans, Past 3M	ECB	% Bal.	6	0	FD
BLS: Chg in Bus Loan Demand, Next 3M, Med/Small Cos	ECB	% Bal.	6	1	FD
BLS: Chg in Bus Loan Demand, Next 3M, Large Cos	ECB	% Bal.	6	1	FD
BLS: Chg in Bus Loan Demand, Next 3M, Short-term	ECB	% Bal.	6	1	FD
BLS: Chg in Bus Loan Demand, Next 3M, Long-term	ECB	% Bal.	6	1	FD
BLS: Chg in HH Demand for Cons Credit, Next 3M	ECB	% Bal.	6	1	FD
BLS: Chg in HH Demand for Housing Loans, Next 3M	ECB	% Bal.	6	1	FD

Note: FW indicates whether a survey series has a forward-looking character (1). FD indicates the first-difference transformation of the series.

Variables included in VAR analysis

- Industrial production: EA20 industrial production (industry excl. construction, SWDA, 2021=100), obtained from Eurostat and transformed as $100 * \log(X)$.
- Retail sales: EA20 retail sales (retails trade volume excl. autos and motorcycles, SWDA, 2021=100), obtained from Eurostat and transformed as $100 * \log(X)$.
- Unemployment: EA20 unemployment rate (SA, %), obtained from Eurostat.
- Policy rate: EA20 main refinancing rate (EOP, %), obtained from the ECB.
- Inflation: EA20 harmonised index of consumer prices (SA, 2015=100), obtained from Eurostat and transformed as $100 * \log(X_t/X_{t-12})$.
- Stock market return: EURO STOXX price index (Dec. 1991=100), obtained from the ECB and transformed as $100 * \log(X_t/X_{t-12})$.
- Composite Indicator of Systemic Stress (CISS): aggregate measure of systemic financial stress in the euro area developed by Hollo et al. (2012), obtained from the ECB.

Other remarks

- All data series, including for the factor extraction, VAR analysis, and out-of-sample forecasting exercise, were retrieved on June 21, 2024 (downloaded from Haver).

Appendix B Additional results

Table B-1: Correlations with hard data, signs of factor loadings, and explanatory power of factors (data, exp. volatility, and exp. skewness)

Survey series	Correlation with hard data								Sign of loadings			Var. expl. by 1st PC of:		
	IP (m/m)		Constr. (m/m)		RS (m/m)		UR (diff.)		Data	Vola	Skew	Data	Vola	Skew
Industry: Production Expectations	0.76	***	0.61	***	0.70	***	0.11	*	+	+	+	76.7	61.4	3.1
Industry: Volume of Order Books	0.39	***	0.15	**	0.17	***	-0.29	***	+	+	+	42.7	71.1	26.4
Industry: Stocks of Finished Products	-0.17	***	0.00		0.05		0.10		-	+	+	13.8	42.9	0.0
Industry: Volume of Export Order Books	0.38	***	0.20	***	0.17	***	-0.27	***	+	+	-	36.1	63.4	14.4
Industry: Selling Price Expectations	0.28	***	0.16	**	0.24	***	-0.13	**	+	+	-	22.4	27.3	20.3
Industry: Production Trend in Recent Months	0.34	***	0.11	*	0.13	**	-0.10		+	+	+	35.3	70.4	33.4
Industry: Employment Expectations	0.62	***	0.40	***	0.44	***	-0.15	**	+	+	+	67.3	72.8	19.9
Consumer: Finan Situation last 12 Mo	-0.06		-0.07		-0.08		-0.19	***	+	+	+	0.5	20.5	53.8
Consumer: Finan Situation next 12 Months	0.49	***	0.38	***	0.49	***	0.05		+	+	+	44.8	65.6	23.6
Consumer: Gen Econ Situation next 12 Mo	0.47	***	0.38	***	0.50	***	0.06		+	+	-	51.8	64.6	5.7
Consumer: Major Purchases next 12 Mo	0.37	***	0.32	***	0.36	***	-0.01		+	+	+	26.0	6.5	0.2
Consumer: HH Fin Situation: Sample Total	0.09		0.10		0.21	***	-0.01		+	+	-	3.7	1.3	9.2
Consumer: Major Purchases at Present	0.55	***	0.55	***	0.63	***	0.06		+	+	+	54.6	74.8	22.5
Consumer: Savings at Present	-0.10		-0.20	***	-0.16	***	0.08		-	-	-	2.1	10.8	0.7
Consumer: Savings over next 12 Months	0.12	*	0.06		0.15	**	0.03		+	-	-	4.7	0.9	0.4
Consumer: Gen Econ Situation last 12 Mo	-0.01		-0.18	***	-0.16	**	-0.32	***	+	+	+	6.8	13.1	31.4
Consumer: Price Trends last 12 Months	0.25	***	0.25	***	0.25	***	-0.26	***	+	+	-	8.5	20.1	3.2
Consumer: Price Trends next 12 Months	-0.13	**	-0.05		-0.08		-0.22	***	-	+	+	1.3	16.5	32.5
Consumer: Unempl Expectations next 12 Mo	-0.47	***	-0.32	***	-0.41	***	0.18	***	-	+	+	61.0	65.8	3.7
Retail: Present Business Situation	0.24	***	0.10		0.08		-0.08		+	+	+	25.0	0.9	47.6
Retail: Volume of Stocks	-0.21	***	-0.21	***	-0.15	**	-0.03		-	+	+	14.2	17.8	34.3
Retail: Expected Business Situation	0.60	***	0.49	***	0.67	***	0.09		+	+	-	70.5	68.4	6.0
Retail: Orders Placed with Suppliers	0.59	***	0.51	***	0.64	***	0.03		+	+	+	72.6	74.8	12.3
Retail: Selling Price Expectations	0.35	***	0.34	***	0.35	***	-0.19	***	+	+	-	23.0	24.2	12.6
Retail: Employment Expectations	0.61	***	0.49	***	0.57	***	0.00		+	+	+	62.9	62.8	41.2
Services: Business Development Over Prev 3 Months	0.38	***	0.17	***	0.20	***	-0.08		+	+	-	41.2	77.2	55.1

Table B-1: Correlations with hard data, signs of factor loadings, and explanatory power of factors (data, exp. volatility, and exp. skewness)

Survey series	Correlation with hard data				Sign of loadings			Var. expl. by 1st PC of:		
	IP (m/m)	Constr. (m/m)	RS (m/m)	UR (diff.)	Data	Vola	Skew	Data	Vola	Skew
Services: Evolution of Demand Over Prev 3 Months	0.32 ***	0.12 *	0.11 *	-0.15 **	+	+	-	31.6	55.3	38.8
Services: Expected Demand Over Next 3 Months	0.72 ***	0.62 ***	0.75 ***	0.11 *	+	+	-	77.9	64.5	6.0
Services: Evolution of Employment Over Prev 3 Months	0.34 ***	0.22 ***	0.18 ***	-0.21 ***	+	+	-	24.3	66.1	28.8
Services: Price Expectations Over Next 3 Months	0.72 ***	0.57 ***	0.65 ***	0.02	+	+	+	75.1	74.6	39.3
Construction: Volume of Order Books	0.47 ***	0.28 ***	0.29 ***	-0.27 ***	+	+	-	44.0	30.0	1.6
Construction: Employment Expectations	0.65 ***	0.48 ***	0.51 ***	-0.08	+	+	-	59.4	65.6	16.5
Construction: Price Expectations	0.29 ***	0.15 **	0.28 ***	-0.15 **	+	+	-	24.6	29.9	5.7
Construction: Trend of Activity , Past 3 months	0.19 ***	-0.03	0.00	-0.14 **	+	+	+	23.8	67.7	28.2
Constr: Factors Limiting Bldg Activity: Demand	0.00	0.06	0.03	0.18 ***	-	+	+	0.5	4.1	7.3
Constr:Limits to Bldg Activity:Weather Conditions	0.07	-0.01	-0.04	0.02	+	-	-	0.1	2.4	19.4
Constr: Limits to Bldg Activity: Labor Shortage	0.34 ***	0.23 ***	0.27 ***	-0.23 ***	+	+	-	19.7	20.7	0.4
Constr: Limits to Bldg Activity: Eqpt Shortage	-0.22 ***	-0.15 **	-0.11 *	-0.09	-	+	+	2.6	13.2	18.7
Constr: Limits to Bldg Activity: Other Factors	-0.63 ***	-0.45 ***	-0.46 ***	-0.03	-	+	+	49.2	15.6	10.8
Constr: Limits to Bldg Activity: Fin Constraints	-0.02	-0.05	-0.11 *	0.06	-	+	+	0.7	5.9	2.4
Euro area: Construction Labor Hoarding	-0.05	-0.03	0.04	0.02	-	-	+	3.3	19.5	0.3
Euro area: Industry Labor Hoarding	-0.71 ***	-0.50 ***	-0.67 ***	-0.15 **	-	+	-	68.6	79.3	21.9
Euro area: Retail Labor Hoarding	-0.44 ***	-0.27 ***	-0.48 ***	-0.06	-	+	-	40.7	64.3	1.2
Euro area: Services Labor Hoarding	-0.60 ***	-0.49 ***	-0.64 ***	-0.13 **	-	+	+	59.8	64.5	0.9
Economic Sentiment, Current Macroeconomic Conditions	0.39 ***	0.21 ***	0.25 ***	-0.23 ***	+	+	+	36.3	25.7	49.5
Econ Sentiment, Macroecon Expectations [Next 6 Mos]	-0.02	0.03	0.08	0.24 ***	+	-	-	1.8	6.6	11.2
Financial Market Survey: Inflation Expectations	0.07	0.09	0.10	0.16 **	+	+	-	2.6	8.0	4.6
Financial Market Survey: S-T Interest Expectations	0.07	0.04	0.01	0.11 *	+	+	+	3.6	4.7	0.4
Financial Market Survey: Stock Mkt Expectations	-0.09	-0.07	-0.10	-0.09	-	+	+	0.0	12.4	11.3
Inst Investors Economic Expectations/Sentiment	0.18 ***	0.14 **	0.17 ***	0.22 ***	+	+	-	11.6	3.0	31.6
Private Investors Economic Expectations/Sentiment	0.17 ***	0.11 *	0.15 **	0.21 ***	+	-	-	15.8	4.1	30.2
Inst Investors Economic Index, Current Situation	0.37 ***	0.18 ***	0.20 ***	-0.11 *	+	+	-	40.0	51.0	0.0

Table B-1: Correlations with hard data, signs of factor loadings, and explanatory power of factors (data, exp. volatility, and exp. skewness)

Survey series	Correlation with hard data								Sign of loadings			Var. expl. by 1st PC of:		
	IP (m/m)		Constr. (m/m)		RS (m/m)		UR (diff.)		Data	Vola	Skew	Data	Vola	Skew
Private Investors Economic Index, Current Situation	0.41	***	0.23	***	0.23	***	-0.10		+	+	+	47.3	46.3	29.2
PMI: Manufacturing Output	0.68	***	0.57	***	0.66	***	0.13	**	+	+	+	71.6	67.8	2.8
PMI: Manufacturing New Orders	0.63	***	0.46	***	0.57	***	0.18	***	+	+	-	73.1	69.1	22.2
PMI: Manufacturing Employment	0.55	***	0.34	***	0.38	***	-0.07		+	+	+	55.8	72.7	7.7
PMI: Manufacturing Suppliers' Delivery Times	0.38	***	0.43	***	0.47	***	0.13	**	+	+	-	8.5	46.7	12.3
PMI: Manufacturing Stocks of Purchases	0.00		-0.08		0.03		-0.17	***	+	+	+	0.6	0.0	18.7
PMI: Manufacturing Input Prices	0.15	**	0.00		0.04		-0.06		+	-	+	8.6	0.5	6.5
PMI: Manufacturing Quantity of Purchases	0.59	***	0.41	***	0.49	***	0.10		+	+	+	69.3	54.3	4.0
PMI: Manufacturing Stocks of Finished Goods	-0.14	**	-0.15	**	-0.08		-0.17	***	-	+	-	9.6	24.7	4.2
PMI: Manufacturing New Export Orders	0.65	***	0.47	***	0.56	***	0.18	***	+	+	-	72.7	74.4	2.0
PMI: Manufacturing Output Prices	0.20	***	0.08		0.13	**	-0.14	**	+	+	-	14.0	9.1	15.4
PMI: Manufacturing Backlogs of Work	0.55	***	0.34	***	0.43	***	0.08		+	+	-	62.1	65.4	14.3
PMI: Manufacturing Orders to Inventories	0.56	***	0.43	***	0.51	***	0.21	***	+	+	+	64.9	70.6	2.2
PMI: Services Employment	0.64	***	0.51	***	0.58	***	0.07		+	+	-	54.4	64.0	1.3
PMI: Services Prices Charged	0.47	***	0.33	***	0.47	***	-0.14	**	+	+	-	35.6	54.4	14.4
PMI: Services New Business	0.62	***	0.58	***	0.72	***	0.15	**	+	+	-	60.8	50.1	34.4
PMI: Services Input Prices	0.36	***	0.31	***	0.33	***	-0.09		+	+	-	23.0	37.1	14.5
PMI: Services New Export Orders	0.67	***	0.55	***	0.68	***	0.12	*	+	+	+	63.1	57.1	22.3
PMI: Services Future Activity	0.38	***	0.40	***	0.43	***	0.18	***	+	+	+	26.8	66.8	33.3
PMI: Construction Housing Activity	0.54	***	0.68	***	0.56	***	0.09		+	+	-	39.2	23.4	3.3
PMI: Construction Commercial Activity	0.61	***	0.71	***	0.63	***	0.06		+	+	-	47.6	35.4	0.1
PMI: Construction Civil Engineering Activity	0.54	***	0.67	***	0.57	***	0.07		+	+	+	33.3	35.4	37.4
PMI: Construction New Orders	0.56	***	0.65	***	0.64	***	0.10		+	+	+	45.3	58.8	3.3
PMI: Construction Employment	0.47	***	0.58	***	0.46	***	0.04		+	+	+	36.6	48.2	1.0
PMI: Construction Quantity of Purchases	0.58	***	0.72	***	0.60	***	0.07		+	+	-	42.8	33.5	14.4
PMI: Construction Delivery Times	0.40	***	0.39	***	0.43	***	0.14	**	+	+	-	11.5	45.7	0.1

Table B-1: Correlations with hard data, signs of factor loadings, and explanatory power of factors (data, exp. volatility, and exp. skewness)

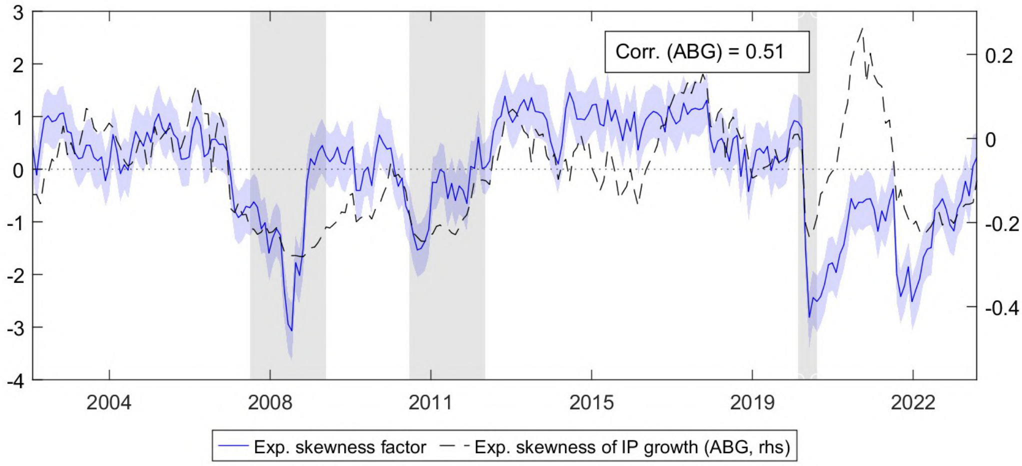
Survey series	Correlation with hard data				Sign of loadings			Var. expl. by 1st PC of:		
	IP (m/m)	Constr. (m/m)	RS (m/m)	UR (diff.)	Data	Vola	Skew	Data	Vola	Skew
PMI: Construction Subcontractor Availability	0.17 ***	0.22 ***	0.32 ***	0.21 ***	+	+	+	0.6	30.0	0.0
PMI: Construction Subcontractor Usage	0.57 ***	0.66 ***	0.55 ***	0.07	+	+	+	41.4	0.6	4.7
PMI: Construction Subcontractor Quality	0.21 ***	0.22 ***	0.21 ***	0.12 *	+	+	+	5.3	1.9	6.4
PMI: Construction Subcontractor Rates	0.26 ***	0.20 ***	0.29 ***	-0.12 *	+	+	+	19.5	28.9	6.0
PMI: Construction Input Prices	0.22 ***	0.09	0.11 *	-0.02	+	+	+	11.8	4.6	11.4
PMI: Construction Business Expectations	0.23 ***	0.25 ***	0.24 ***	0.11 *	+	-	-	12.7	14.0	31.7
PMI: Manufacturing Capacity Utilization	-0.07	-0.21 ***	-0.20 ***	-0.07	+	+	-	1.7	7.6	44.2
Productivity: Manufacturing & Services	0.51 ***	0.56 ***	0.69 ***	0.19 ***	+	+	+	41.2	61.0	28.6
BLS: Chg in Credit Stds for Bus Lns to Med/Sm Cos, Past 3M	-0.03	0.01	-0.01	0.01	-	+	+	1.1	3.8	8.7
BLS: Chg in Credit Stds for Bus Lns to Large Cos Past 3M	0.01	0.03	0.01	-0.03	-	+	+	1.4	4.0	6.0
BLS: Chg in Credit Stds for Short-term Bus Lns, Past 3M	0.02	0.07	0.02	-0.01	-	+	+	0.7	6.2	14.9
BLS: Chg in Credit Stds for Long-term Bus Lns, Past 3M	0.00	0.04	0.01	0.03	-	+	+	1.2	3.4	14.1
BLS: Chg in Cr Stds, Past 3M, Apprv Cons Cr/Oth Ldg	-0.14 **	-0.02	-0.04	0.16 ***	-	+	+	3.2	9.2	7.2
BLS: Chg in Cr Stds, Past 3M, Apprv House Purch Lns	-0.03	0.03	0.01	0.16 **	-	+	+	2.3	2.6	5.2
BLS: Chg in Credit Stds for Bus Lns to Ned/Sm Cos, Next 3M	0.02	-0.02	-0.04	0.06	-	+	+	0.0	18.6	2.5
BLS: Chg in Credit Stds for Bus Lns to Large Cos Next 3M	0.04	0.00	-0.02	0.02	-	+	+	0.1	11.8	2.0
BLS: Chg in Credit Stds for Short-term Bus Lns, Next 3M	0.04	0.02	-0.03	0.04	+	+	+	0.0	20.2	0.2
BLS: Chg in Credit Stds for Long-term Bus Lns, Next 3M	0.01	0.02	-0.02	0.04	-	+	+	1.2	8.5	5.3
BLS: Chg in Cr Stds, Next 3M, Apprv Cons Cr/Oth Ldg	-0.08	-0.01	0.02	0.05	-	+	+	3.7	16.7	7.7
BLS: Chg in Cr Stds, Next 3M, Apprv House Purch Lns	-0.03	-0.02	0.03	0.04	-	+	+	1.8	10.0	3.7
BLS: Chg in Bus Loan Demand, Past 3M, Med/Small Cos	0.03	0.00	0.05	0.02	+	+	-	0.7	15.5	4.0
BLS: Chg in Bus Loan Demand, Past 3M, Large Cos	0.01	0.00	0.07	0.06	+	+	-	0.4	13.6	3.8
BLS: Chg in Bus Loan Demand, Past 3M, Short-term	-0.03	-0.03	0.05	0.08	-	+	-	0.2	12.6	1.6
BLS: Chg in Bus Loan Demand, Past 3M, Long-term	0.05	-0.01	0.01	-0.13 **	+	+	-	1.6	2.6	8.5
BLS: Chg in HH Demand for Cons Credit, Past 3M	0.06	-0.04	-0.05	-0.28 ***	+	+	-	0.0	8.3	4.2
BLS: Chg in HH Demand for Housing Loans, Past 3M	0.03	-0.04	-0.06	-0.15 **	+	+	-	0.1	5.9	4.1

Table B-1: Correlations with hard data, signs of factor loadings, and explanatory power of factors (data, exp. volatility, and exp. skewness)

Survey series	**Correlation with hard data**				**Sign of loadings**			**Var. expl. by 1st PC of:**		
	IP (m/m)	**Constr. (m/m)**	**RS (m/m)**	**UR (diff.)**	**Data**	**Vola**	**Skew**	**Data**	**Vola**	**Skew**
BLS: Chg in Bus Loan Demand, Next 3M, Med/Small Cos	0.02	0.10	0.15 **	0.09	-	+	-	0.0	53.9	7.1
BLS: Chg in Bus Loan Demand, Next 3M, Large Cos	0.00	0.08	0.15 **	0.08	-	+	-	0.4	43.4	5.4
BLS: Chg in Bus Loan Demand, Next 3M, Short-term	-0.04	0.05	0.11 *	0.09	-	+	-	1.2	55.3	0.7
BLS: Chg in Bus Loan Demand, Next 3M, Long-term	0.07	0.02	0.09	-0.05	+	+	-	0.9	13.5	4.7
BLS: Chg in HH Demand for Cons Credit, Next 3M	0.09	-0.05	-0.05	-0.01	+	+	-	6.4	31.8	10.3
BLS: Chg in HH Demand for Housing Loans, Next 3M	0.04	-0.06	-0.08	0.02	+	+	-	5.5	29.7	7.8

Note: This table shows the correlations of each survey series with different hard economic indicators, i.e. the monthly growth rates (in %) of industrial production, construction activity, and retail sales, as well as the monthly change in the unemployment rate. The *, **, and *** denote significance of the correlations at the 10%, 5%, and 1% level, respectively. The table also contains the signs of the factor loadings of each survey series with respect to the first principal components of the data (Figure B-2), expected volatility (Figure B-3), and expected skewness (Figure 1). The last three columns of the table show the shares of variation for each series (in %), its expected volatility, and its expected skewness explained by the respective first principal component.

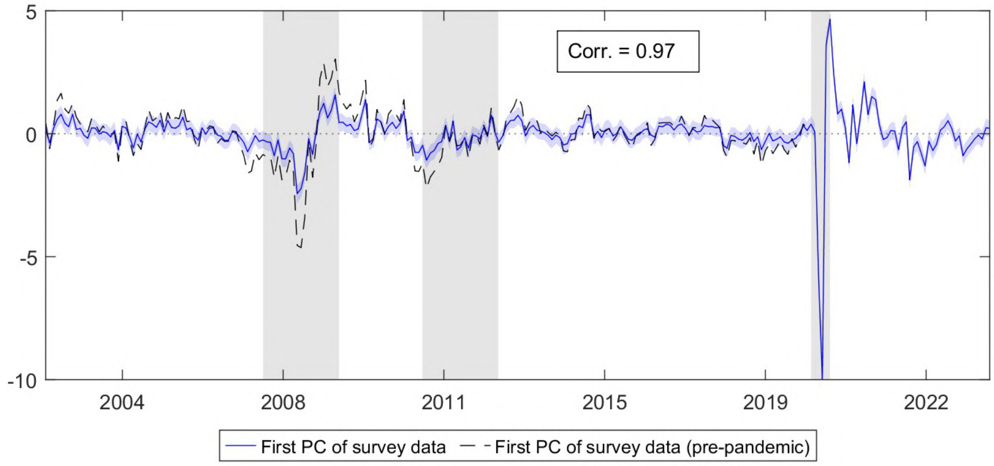
Figure B-1: Exp. skewness factor vs. exp. skewness of IP growth (ABG)



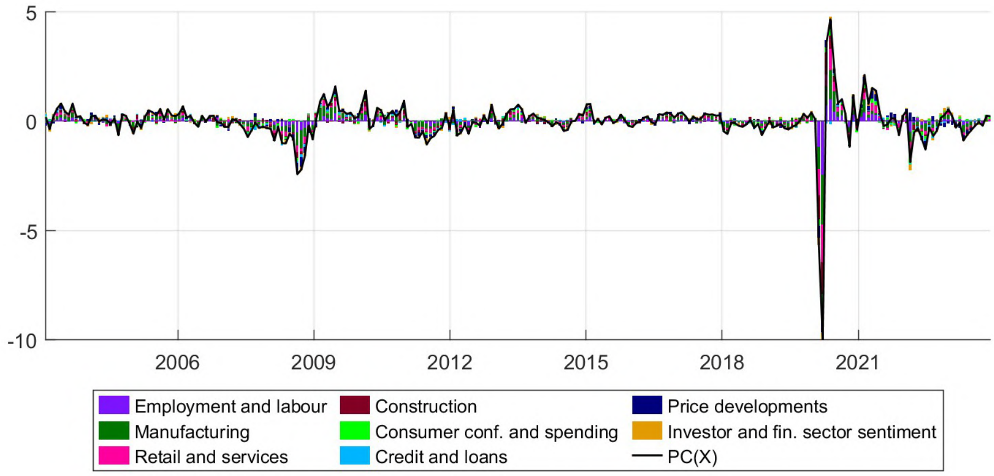
Note: This figure compares the exp. skewness factor with the exp. skewness of industrial production growth, where the latter is computed based on a model in the spirit of Adrian et al. (2019) (ABG). In particular, it reflects the Kelley skewness obtained from quantile regressions of the average 3-month-ahead month-over-month growth rate of industrial production on a constant, the current euro area manufacturing PMI, as well as the current level of the ECB's Composite Indicator of Systemic Stress (Hollo et al., 2012). The coefficients of these quantile regressions are estimated over the period 04/2003–12/2019. The blue shaded areas are the bootstrapped confidence bands (90%) around the skewness factor based on Gonçalves and Perron (2020). Gray areas are recessions as dated by the EABCN.

Figure B-2: Survey-based common factor

(a) First principal component of survey data



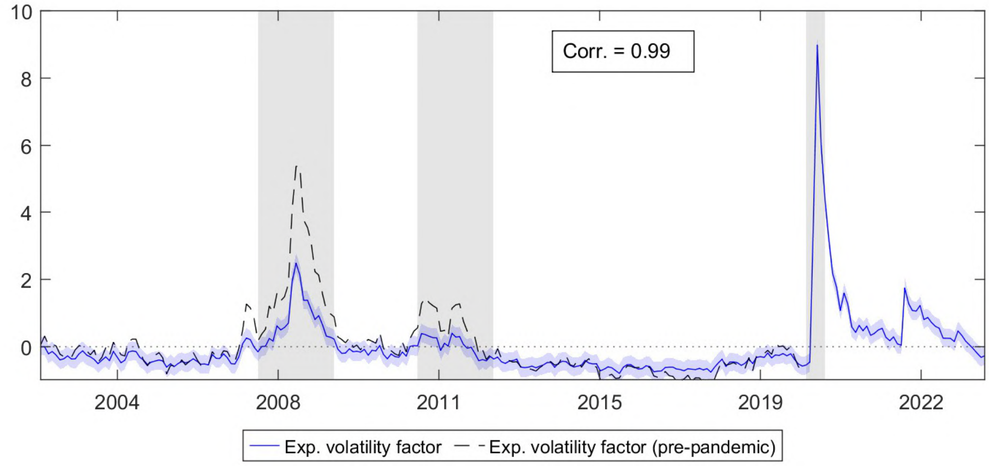
(b) Contributions by groups of variables



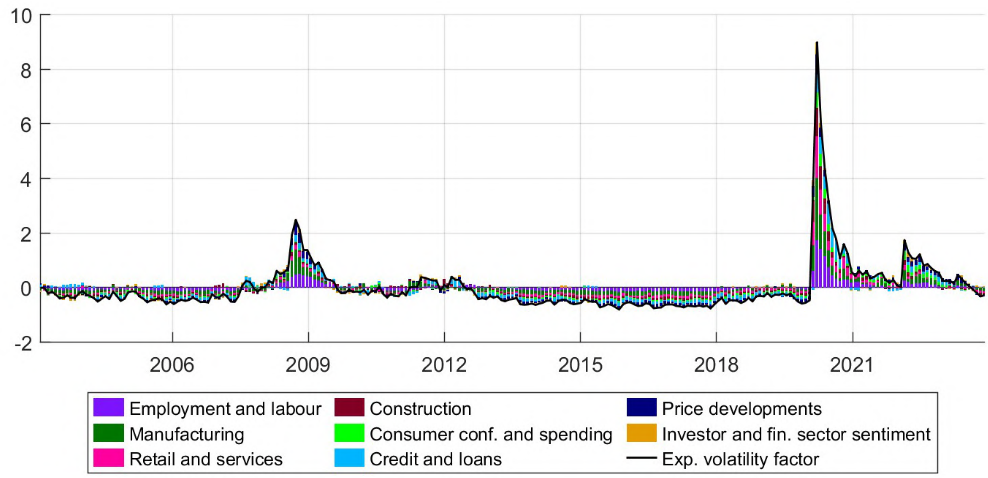
Note: See Figure 1.

Figure B-3: Survey-based volatility factor

(a) First principal component of exp. volatility



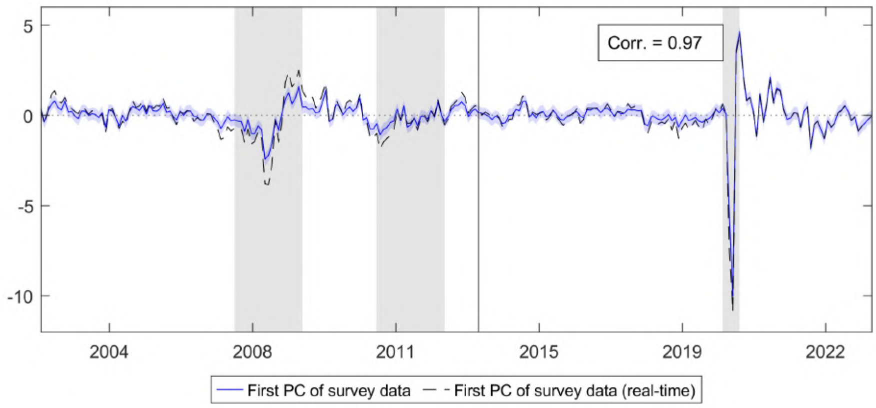
(b) Contributions by groups of variables



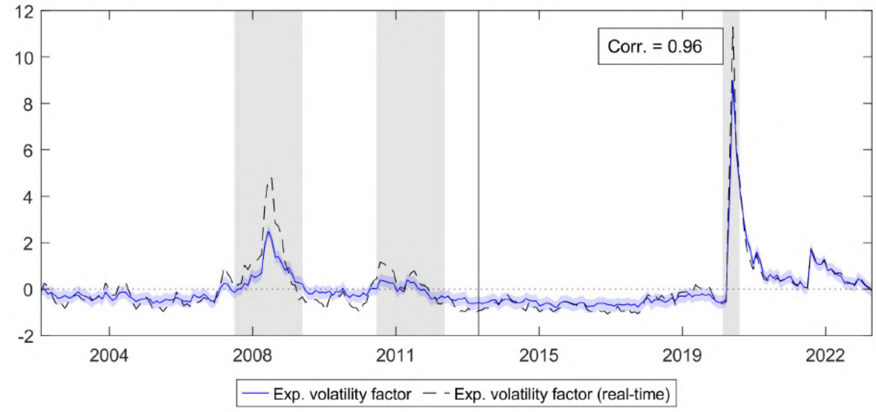
Note: See Figure 1.

Figure B-4: Principal components (full-sample vs. real-time estimates)

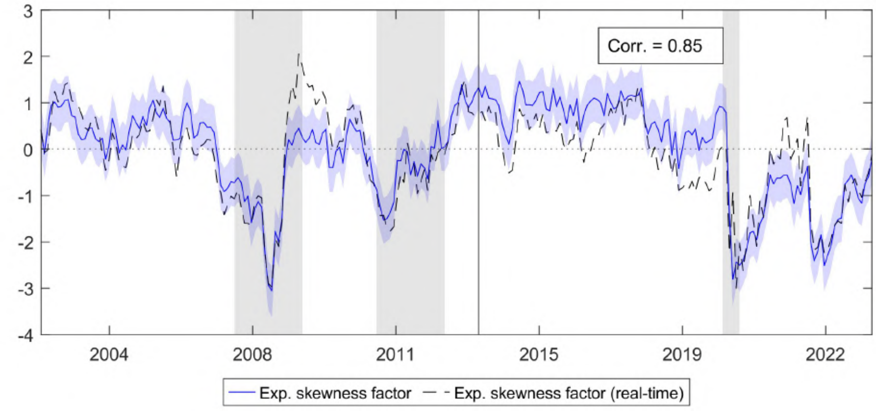
(a) First principal component of the survey data



(b) First principal component of the expected volatility series



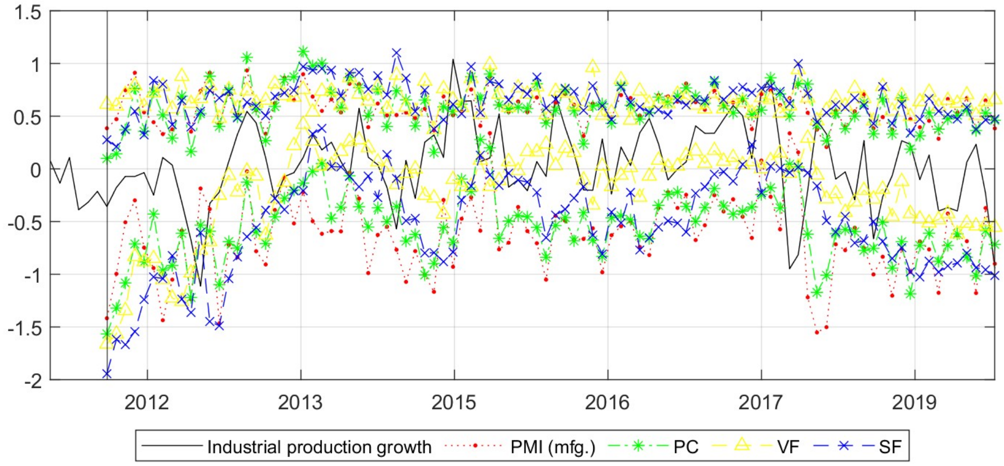
(c) First principal component of the expected skewness series



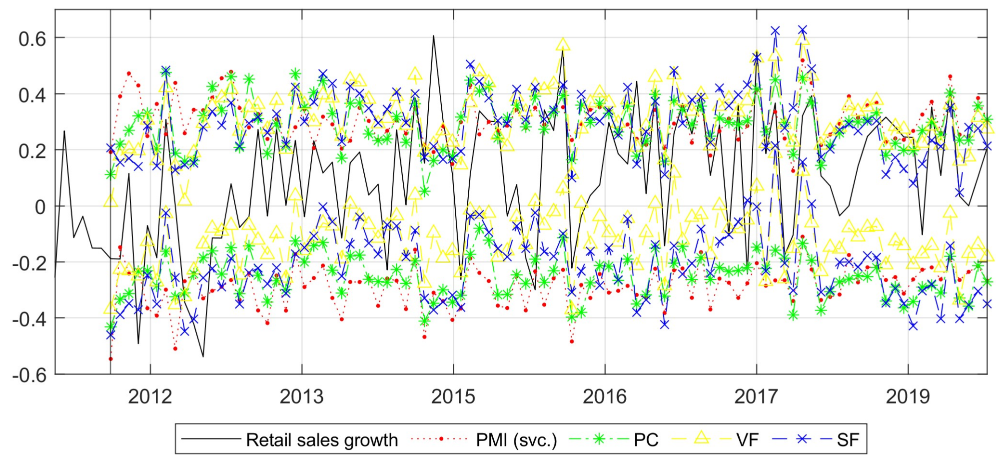
Note: The figures show the first principal components of the survey data, the expected volatility series, and the expected skewness series, respectively, both when estimated over the full sample (04/2003–12/2023) and when estimated recursively (in real time), starting from 10/2013 (vertical black line).

Figure B-5: Results of out-of-sample forecasting exercise (pre-Covid sample, $h = 3$)

(a) Industrial production: Predicted 10% and 90% quantiles for selected models



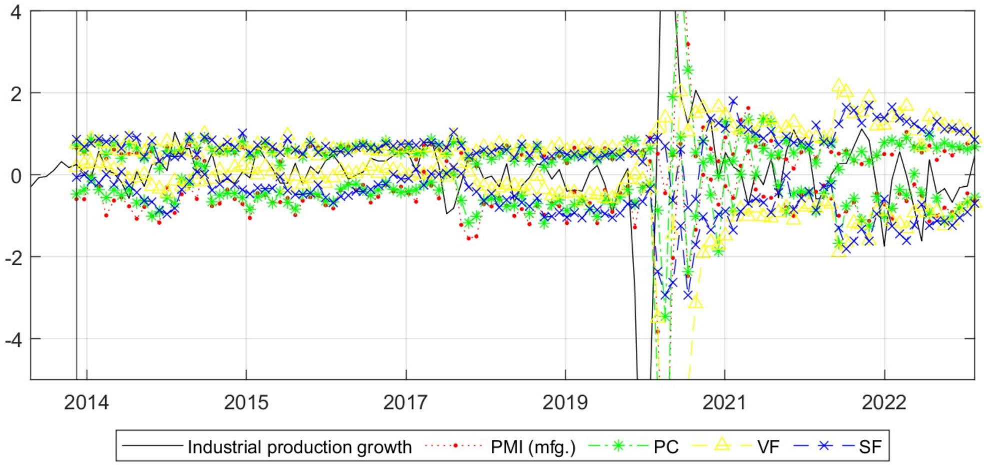
(b) Retail sales: Predicted 10% and 90% quantiles for selected models



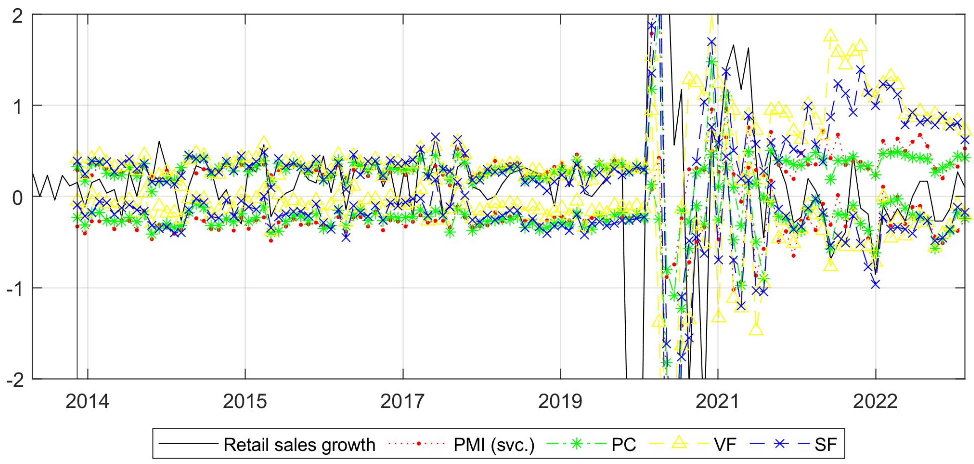
Note: The figures show the predicted 10% and 90% quantiles for the average (month-over-month) growth rate of industrial production and retail sales (three-month-ahead) based on selected models and Equation (3).

Figure B-6: Results of out-of-sample forecasting exercise (full sample, $h = 3$)

(a) Industrial production: Predicted 10% and 90% quantiles for selected models



(b) Retail sales: Predicted 10% and 90% quantiles for selected models



Note: The figures show the predicted 10% and 90% quantiles for the average (month-over-month) growth rate of industrial production and retail sales (three-month-ahead) based on selected models and Equation (3).

Table B-2: Results of out-of-sample forecasting exercise ($h = 6$)

			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*
Industrial production	*I*	Benchmark	0.08	0.11	0.12	0.10	**0.05**	0.16	**0.21**	**0.23**	0.21	0.15
	II	PMI (mfg.)	0.08	0.10 ***	0.12	**0.09** *	**0.05**	0.18	0.22	0.24	**0.20**	0.14
	III	PC	**0.06** ***	**0.09** ***	**0.11** *	**0.09**	**0.05**	0.17	0.22	0.25	0.22	0.16
	IV	VF	0.07	0.10	0.13	0.10	**0.05**	0.19	0.26	0.31	0.23	**0.12**
	V	SF	0.07 *	0.11	0.12	0.10	**0.05**	**0.15** *	**0.21**	0.24	0.23	0.17
	VI	PC + SF	0.07 **	**0.09** **	**0.11**	**0.09**	**0.05**	0.16	0.22	0.26	0.23	0.17
	VII	PC + SF + VF	0.07	**0.09**	**0.11**	**0.09**	**0.05**	0.17	0.23	0.27	**0.20**	**0.12**
Retail sales	*I*	Benchmark	0.03	0.06	0.06	**0.04**	**0.02**	0.10	0.14	**0.16**	**0.14**	**0.12**
	II	PMI (svc.)	0.03	0.06	0.06	**0.04**	**0.02**	0.10 **	0.14	0.17	**0.14**	**0.12**
	III	PC	0.03	0.05 **	0.07	0.05	**0.02**	0.10	0.14	0.17	0.16	0.13
	IV	VF	**0.02** ***	**0.04** ***	**0.05** ***	**0.04**	**0.02**	0.09 **	0.13 *	**0.16**	0.18	0.15
	V	SF	0.03 ***	0.05 ***	0.06	0.05	0.03	**0.08** **	**0.12** ***	**0.16**	0.15	0.13
	VI	PC + SF	0.03 ***	0.05 **	0.06	0.05	**0.02**	**0.08** ***	**0.12** **	**0.16**	0.17	0.15
	VII	PC + SF + VF	**0.02** ***	**0.04** ***	**0.05** *	**0.04**	**0.02**	**0.08** ***	**0.12** **	0.17	0.19	0.17

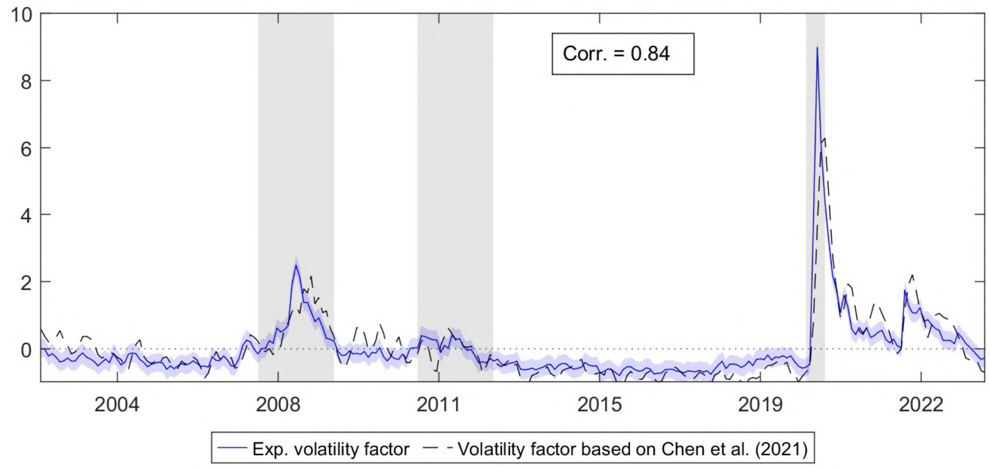
Note: This table reports the quantile scores for a selection of (conditional) quantiles and various model specifications. The dependent variable is the (avg.) month-on-month growth rate of industrial production and retail sales, respectively, $h = 6$ months ahead. PC, VF, and SF are, respectively, the first principal component of the data, expected volatility, and expected skewness. Model I is our benchmark model. Quantile scores reported in bold are the lowest ones for a specific quantile. Each model II to VII also includes current and lagged growth of industrial production/retail sales. ***, **, and * indicate that a specific model outperforms the benchmark based on Diebold and Mariano (1995) tests (using Newey and West (1987) standard errors with lag truncation $h - 1$) at the 1%, 5%, and 10% level, respectively.

Appendix C Robustness checks

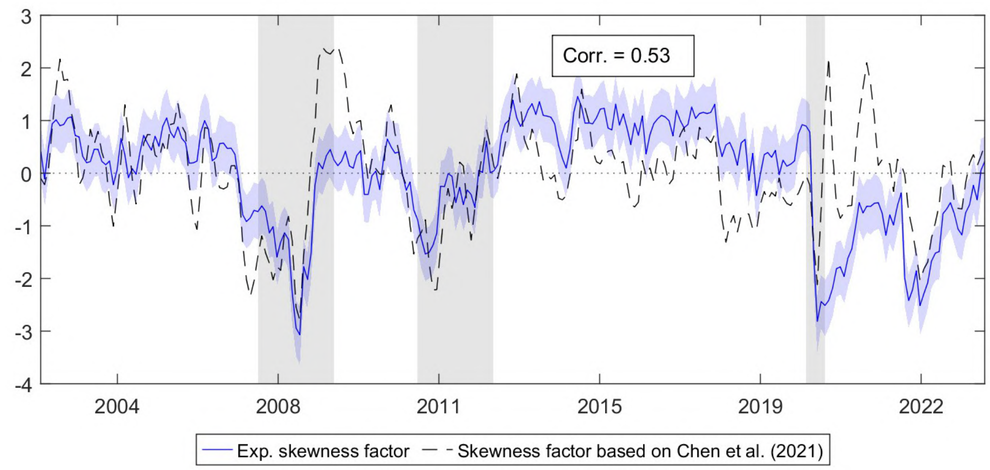
Quantile specification and factor extraction: comparison with Chen et al. (2021)

Figure C-1: Survey-based (exp.) volatility and (exp.) skewness factor

(a) Volatility factor: comparison with Chen et al. (2021)



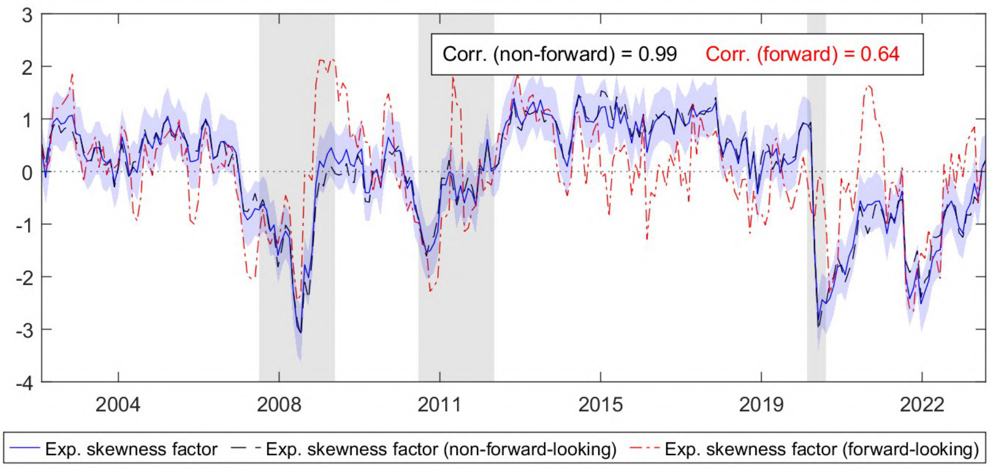
(b) Skewness factor: comparison with Chen et al. (2021)



Note: Figures C-1(a) and C-1(b) compare the exp. volatility and skewness factor derived from the approach of Iseringhausen et al. (2023) (see Section 2.2) and the quantile factor model of Chen et al. (2021). For the latter, we use the MATLAB code of the authors and three factors to obtain the fitted quantiles. These are then used to compute the sets of series-specific interquartile ranges and Kelley skewness. Following Iseringhausen et al. (2023), the volatility and skewness factor are then computed as the first principal component of these sets (two-month moving average). The blue shaded areas are the bootstrapped confidence bands (90%) around our baseline volatility and skewness factors based on Gonçalves and Perron (2020). Gray areas are recessions as dated by the EABCN.

Skewness factor extracted from forward vs. non-forward looking survey series

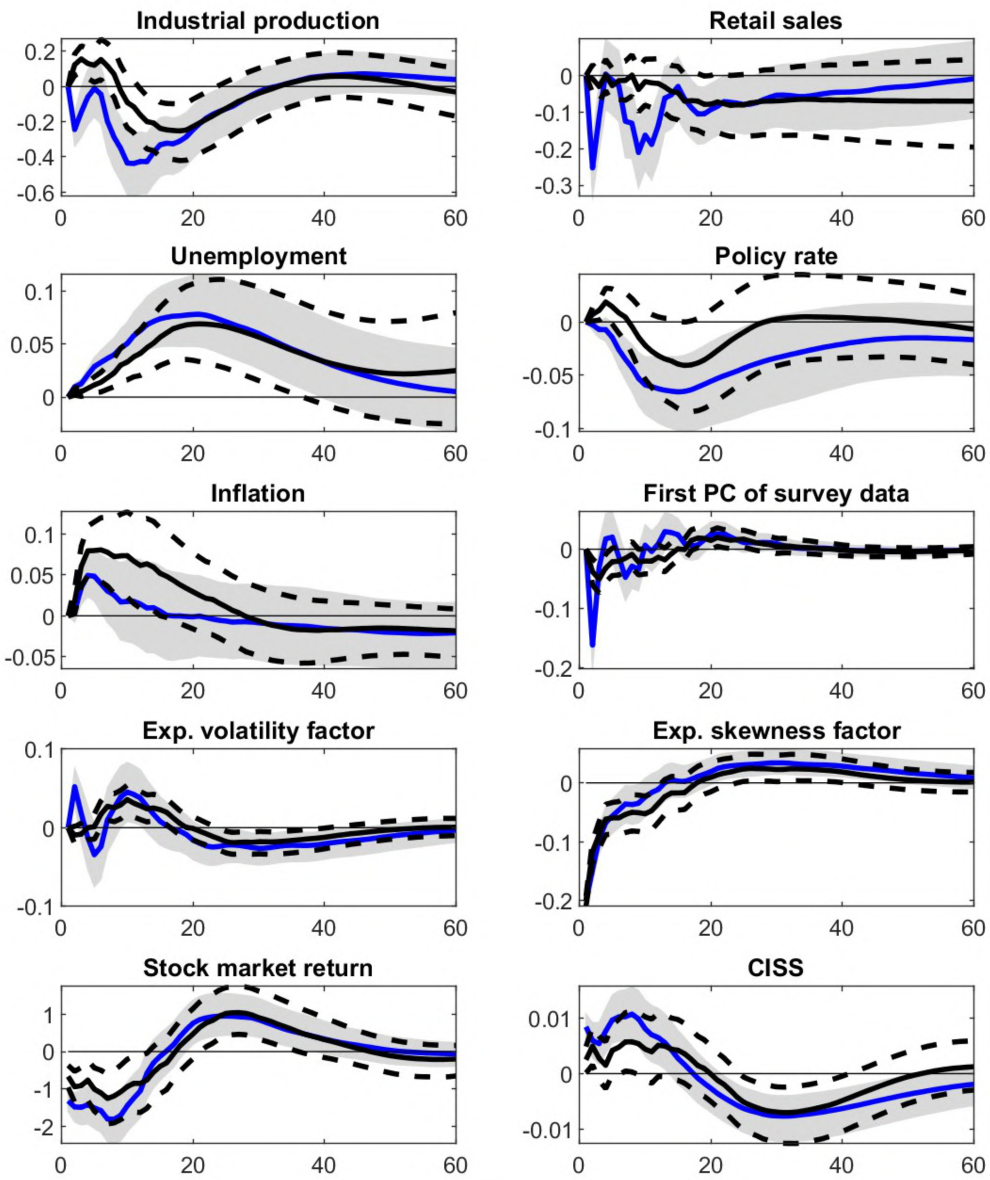
Figure C-2: Skewness factors (forward vs. non-forward looking survey series)



Note: This figure compares the baseline exp. skewness factor obtained from the full set of survey series with alternative skewness factors using only series based on forward-looking questions (36/110) and the remaining (non-forward-looking) series (74/110), respectively. The blue shaded areas are the bootstrapped confidence bands (90%) around the baseline skewness factor based on Gonçalves and Perron (2020). Gray areas are recessions as dated by the EABCN.

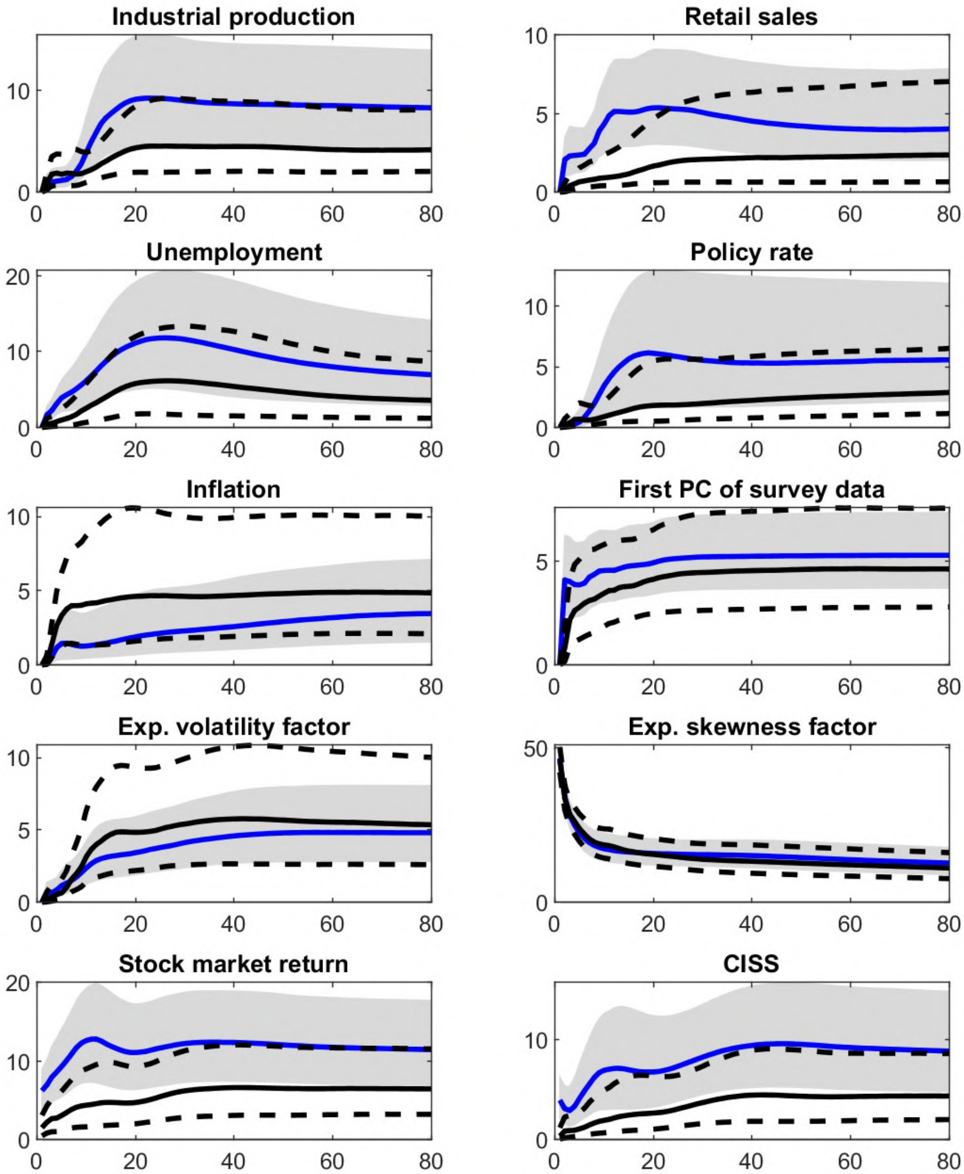
VAR: Alternative ordering of variables for Cholesky identification

Figure C-3: Impulse response functions



Note: See Figure 2.

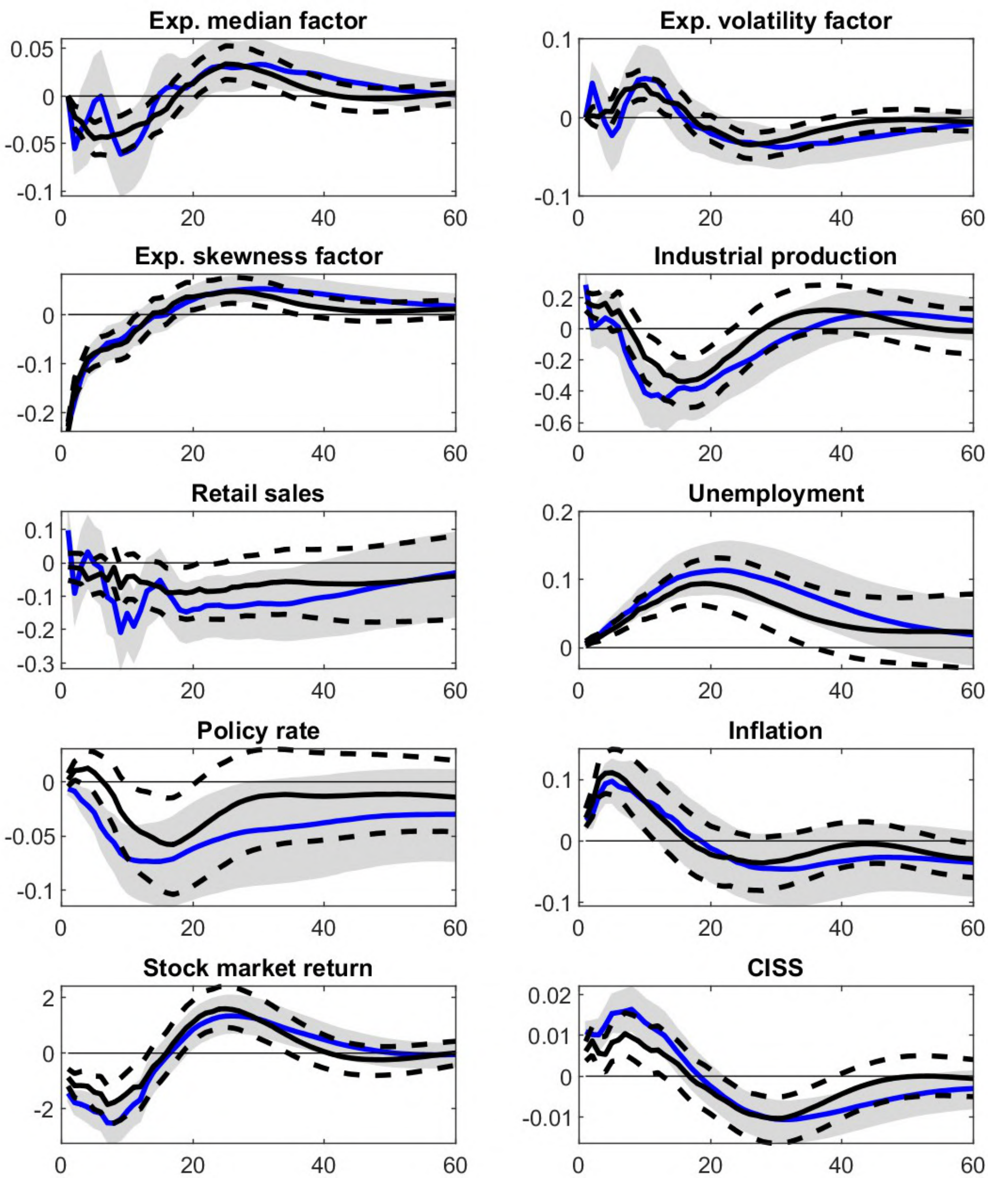
Figure C-4: Forecast error variance contributions



Note: See Figure 3.

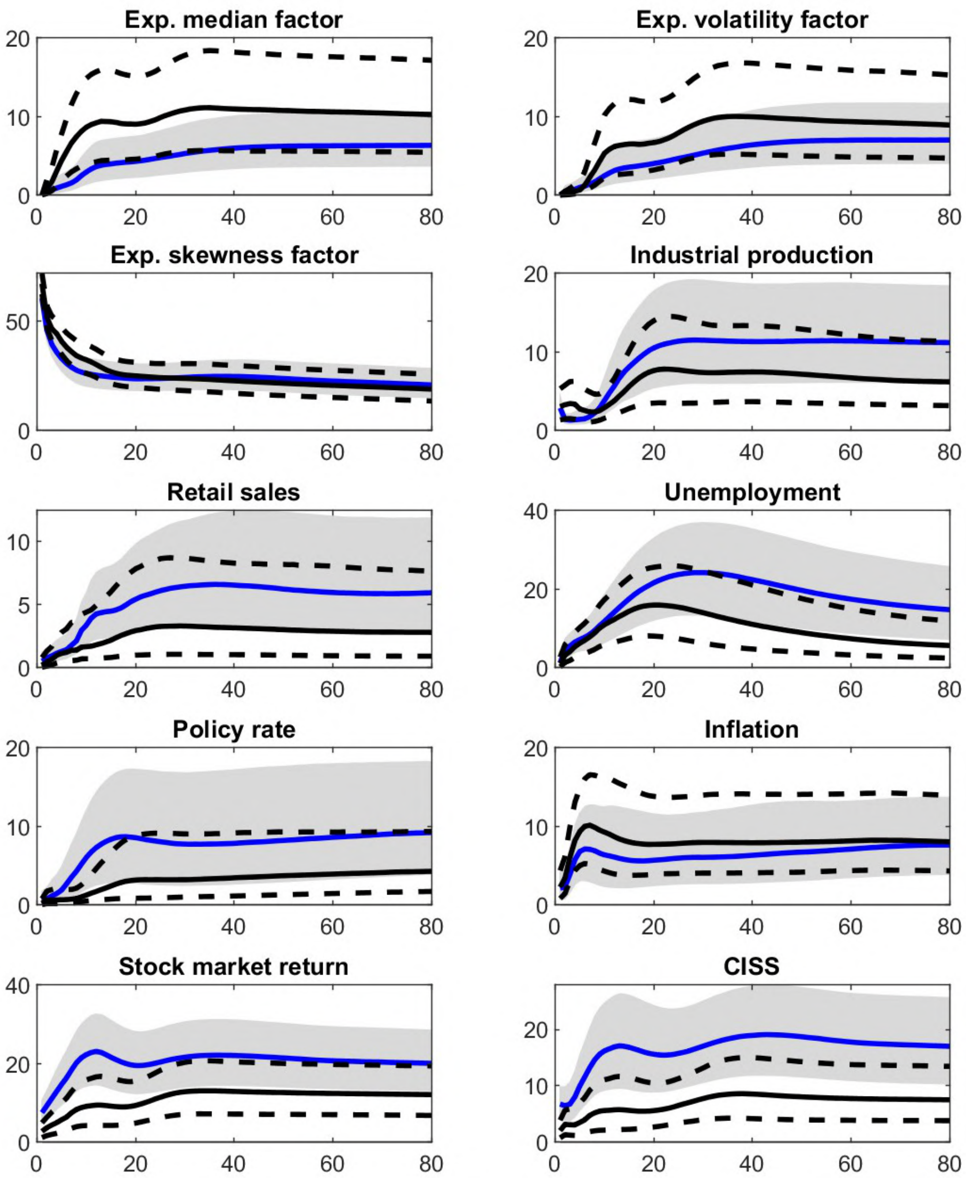
VAR: Replacing the first PC of survey data with expected median factor

Figure C-5: Impulse response functions



Note: See Figure 2.

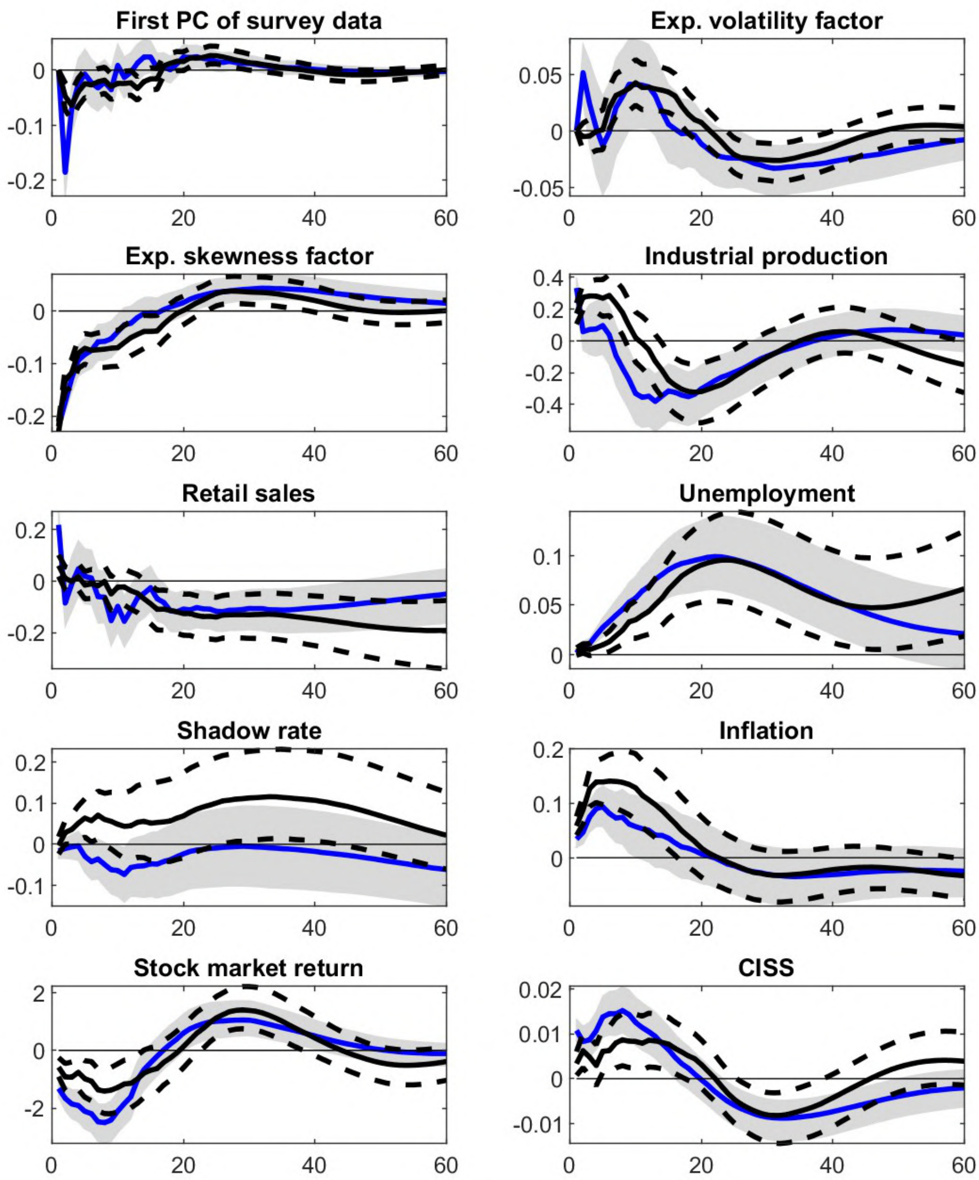
Figure C-6: Forecast error variance contributions



Note: See Figure 3.

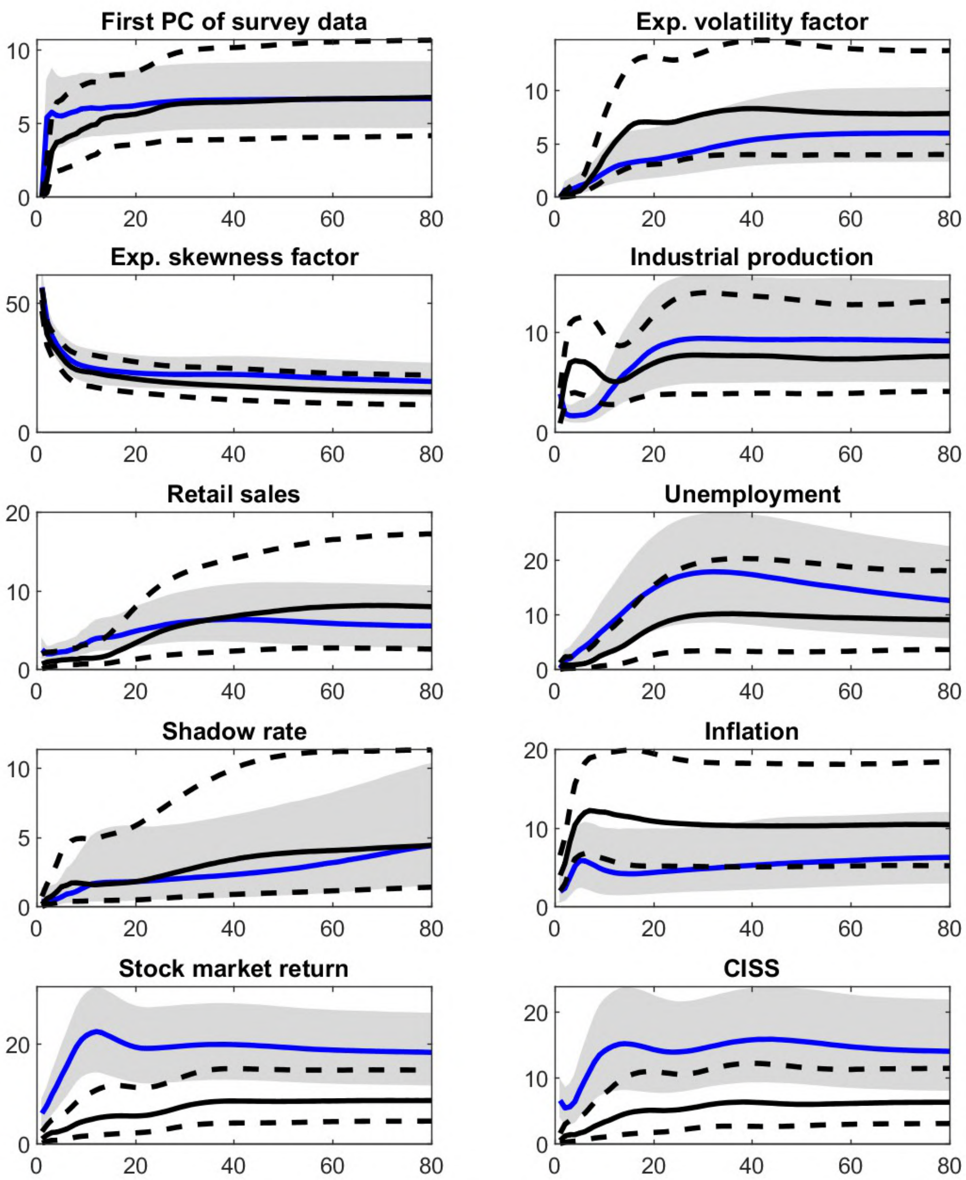
VAR: Replacing the policy rate with the Wu and Xia (2020) shadow rate

Figure C-7: Impulse response functions



Note: See Figure 2.

Figure C-8: Forecast error variance contributions



Note: See Figure 3.